



The drivers of energy access:
Evidence from solar energy applications in Guinea-Bissau

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Abstract

This thesis aims to explore how some of the findings from behavioural economics and the social capital literature can apply in the case of electricity access in developing countries with a focus on solar off-grid electrification. And specifically on solar home systems and solar hybrid mini-grid electrification in rural Guinea-Bissau.

Specifically, I am drawing from studies looking at the role of discounting anomalies on technology adoption and recurring payments, the role of trust on technology adoption and the role of computational limitations and the use of simplification strategies on the accuracy of frequency and expenditure reporting in surveys.

This exercise aims to inform electrification policy in developing countries, demonstrate instances where insights from behavioural economics and social capital can enrich our understanding of the underlying barriers and drivers of electrification access, but also demonstrate how some selected case studies can help to strengthen empirical findings from other contexts.

Chapter 1 provides an introduction on the issues surrounding electrification access in developing countries and introduces the research motivation and the research objectives of this thesis. This chapter also discusses the relevant gaps in the literature, how this thesis attempts to address them and the contribution to knowledge. Finally, the research location is introduced.

Chapter 2 presents the results of a stated preference study that uses a choice experiment to estimate willingness to pay for a solar home system, and the trade-off between different repayment schemes and maintenance responsibilities, in the region of Bafatá in Guinea-Bissau. Results suggest that preferences are driven both by income constraints as well as self-control problems, excessive discounting and self-reported trust for a number of actors.

Chapter 3 explores the main determinants in the decision to connect to a solar hybrid mini-grid, in the semi-urban community of Bambadinca in Guinea-Bissau, with a focus on social capital as expressed in trust. Connections are driven largely by the socio-economic background of the households and prior energy use patterns. However, there is evidence that social capital as expressed in self-reported trust for one's neighbours, also has a positive effect on connections through facilitating the informal expansion of the grid, whereby households use their neighbours' infrastructure to connect to the service.

Chapter 4 explores how the technology of prepaid meters can help researchers acquire more insight regarding the accuracy of survey responses and the response strategies used. More specifically, this chapter tests the accuracy of reported energy expenditure in surveys, when

using differently defined recall periods, namely a ‘usual’ week versus a ‘specific’ (i.e. last) week. We compare real expenditure data for prepaid meters for electricity, from a solar hybrid mini-grid operating in the semi-urban community of Bambadinca in Guinea-Bissau, with answers from a survey where respondents are asked to state their expenditures, randomly, in different recall periods. Overall, our results show that respondents tend to over-report the level and frequency of their energy expenditures, but reporting is more accurate when the ‘specific’ period rather than when the ‘usual’ period is used.

Chapter 5 investigates the role of self-control problems on prepayment patterns for electricity provided by a solar hybrid mini-grid installed in the semi-urban community of Bambadinca in Guinea-Bissau. Prepayment patterns are found to be mostly driven by income constraints and equipment in use however there is evidence that individuals with self-control problems as well as individuals being charged with an additional time-varying tariff (a higher tariff between 7pm to 12am) resort to smaller refill levels possibly as a strategy to consume less electricity at home.

Chapter 6 provides concluding remarks.

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Chapter 1

Introduction

1. Introduction

Achieving universal access to modern energy, which entails efficient lighting, heating, cooking, mechanical power, transport and telecommunication services is a pressing challenge both for development and environmental policy. Universal electrification is central to achieving energy access however, currently over 1.2 billion people are without access to electricity (World Energy Outlook energy access database)¹ and they resort to inefficient alternatives (e.g. kerosene lamps, candles, batteries, generators) that are of lower quality and often costlier (Grimm, Munyehirwe, Peters, & Sievert, 2016). This problem is more pronounced within the rural areas of developing countries and especially in Sub-Saharan Africa where 632 million people live without electricity and the rural electrification rate reaches a meagre 19% (World Energy Outlook energy access database). This situation impedes development and poses various health and safety threats.

Access to electricity is a necessary condition for development as it has a positive impact on several of its determinants namely economic growth, environmental quality, health, education and security.

A reliable source of power can affect economic growth directly as the operation of electrical appliances increases productivity, and better lighting allows for extended working hours, and indirectly through human capital development (e.g. health and education). Educational opportunities are enhanced with more efficient lighting at schools and extended time available to study at home. Health is positively affected as electricity improves the quality of the health services available, through lighting and refrigeration at hospitals, and reduces the dependence on substitutes that are responsible for indoor air pollution (e.g. kerosene lamps). Access to electricity also lessens the reliance on disposable batteries, kerosene lamps and generators which are often responsible for local pollution. Finally, the availability of street

¹ There is no universal definition of what constitutes access to electricity. The international energy agency defines the minimum level to be primarily 250 kilowatt-hours (kWh) per year for households in rural areas and 500 kWh per year for households in urban areas (5 people per household are assumed). This corresponds to the use of a fan, a mobile phone, and two compact fluorescent light bulbs for five hours per day in rural areas and an additional mobile phone, a fridge, and a small television for urban areas. However, for the electricity access database, a binary distinction of electricity access is used due to data limitations (World Energy Outlook defining and modelling energy access).

lighting at night can increase security. (See Bonan, Pareglio, & Tavoni, 2017 for a discussion on findings and challenges of impact evaluations)

The importance of access to electricity for development has also been recognized both by national governments and the international community. A number of international organizations and initiatives have emerged (e.g. Sustainable Energy for All initiative, Lighting Africa initiative) with recent breakthroughs including the addition of energy access in the UN Sustainable Development Goals in 2015 and the acknowledgement of the importance of energy access in the Paris Agreement.

Despite these efforts, the situation is expected to improve only modestly by 2030 (WEO, 2016). The main challenges often cited is lack of investments. As stated by the International Energy Agency (IEA) the additional investment required to achieve universal access to electricity is estimated to be around \$640 billion between 2010 and 2030 (WEO, 2011).

However, the challenge is not only to increase the levels of investment, but also to design electrification initiatives and programs in ways that address potential barriers both from the supply and the demand side, and better meet the needs and preferences of the households currently lacking access.

Policy makers, predominantly focus on extending the grid and on increasing connections to the main grid and the majority of the funding goes to large scale infrastructural projects (WEO, 2011). Nevertheless, grid expansion is not always feasible, especially when it comes to reaching isolated rural areas in developing countries. In these instances, small-scale off-grid technologies have been proven to be more cost effective and easier to implement. These technologies can be installed at the community level (mini-grids) or at the household level (isolated off-grid solutions). In contrast to centralized grids, these small-scale off-grid solutions rely heavily on renewable energy (solar home systems, solar lanterns, wind turbines, biogas installations, pico/micro hydro power, biofuel powered generators, solar mini-grids) and these, therefore, have the possibility to address both social and environmental considerations. In addition, such applications can help boost the clean technology industry creating positive spill-overs for both developing and developed countries.

According to the International Energy Agency, as the major part of people lacking electricity access are located within rural areas to gain access to universal energy, most of the additional investment must be channelled into mini-grid and isolated off-grid projects, which will predominantly be based on renewable energy (WEO, 2011).

There are also a number of barriers to electrification from the demand side. Despite high demand for electrification in developing countries, and despite the fact that electricity substitutes often constitute a higher burden on the budgets of non-electrified households (Bernard, 2010), even households that are close to the grid often fail to make connections that require high upfront payments (Lee, Miguel, & Wolfram, 2016). In addition, connected households often fail to meet recurring payments for electrification (Jack & Smith, 2015) and to purchase the appliances they need or to undertake proper efficiency investments (Bernard, 2010; Jordan, Corry, & Jaques, 2017).

A number of policy solutions have been suggested to address these demand barriers. For example, credit and rental schemes have been put in place in order to reduce the barriers of high one-off costs associated with electricity connections and the purchase of appliances. These are common in the market of solar home systems. In addition, prepaid meters are increasingly being used as a billing alternative for electricity that will help reduce instances of non-payment and allow consumers to have more control over their expenditures. However, the literature looking at the effect of these policies is still scant.

Addressing demand barriers properly requires, first and foremost, an understanding of their underlying determinants and how these interact with different policy solutions and the different technologies available.

2.1 Research motivation

Technology adoption studies have cited potential barriers to adoption decisions for a number of products (e.g. fertilizers, water filters) in developing countries as well as for energy efficiency investments in developed countries drawing from both standard and non-standard models of individual choice.

Rational choice theory within neoclassical economics is based on assumptions of pure self-interest and unbounded rationality. However, a number of systematic deviations from the predictions of this standard economic approach have been observed empirically. These deviations demonstrate the systematic presence of irrationalities and the influence of the social context in decision making. This has led to the need for alternative paradigms in order to capture more accurately the process of human decision making.

Behavioural economics is a strand of economics that incorporates insights from psychology to systematize and synthesize departures from the standard economic model of decision making.

The underlying explanations behind these departures are known as behavioural biases, anomalies or principles. These departures can be classified in three clusters: bounded rationality, bounded willpower and bounded self-interest² (Mullainathan & Thaler, 2000).

Bounded rationality refers to the inability of the human brain due to reference dependent preferences, loss aversion, limited attention, limited computational capacity or biased reasoning to process information correctly in order to make optimal choices between alternatives. Bounded willpower refers to the inability of humans to actually make the right choice even if they know what it is. This is due to the presence of time inconsistent preferences. Finally, bounded self-interest refers to individual preferences being affected by considerations of the well-being of others or other social context (altruism, fairness, social norms, and interpersonal preferences).

A number of detailed reviews on behavioural economics and their application are available (DellaVigna, 2009; Mullainathan & Thaler, 2000; Rabin, 1998). In the following sections I discuss the behavioural biases that are relevant to this thesis in more detail.

The social capital literature has also looked at the importance of the social context in decision making. Durlauf & Fafchamps, 2005 discuss the importance of social capital in

² Other classifications have also emerged e.g. imperfect optimization, bounded self-control and non-standard preferences (Congdon, Kling, & Mullainathan, 2011). Non-standard beliefs, non-standard decision making, non-standard preferences (DellaVigna, 2009).

dealing with inefficiencies caused from externalities, free riding, imperfect information and imperfect enforcement. This is achieved as social capital can address problems of coordination, change the motives of individuals and create opportunities for the flow of information.

There are multiple definitions of social capital and ways that it has been measured in the literature (size and type of networks, membership in associations, norms, trust) (Knack & Keefer, 1997).

Trust is one of the indicators that have been used from scholars to measure social capital. Some scholars see trust as a component of social capital. For example, in Putnam's seminal work social capital is defined as "features of social organization, such as networks, norms and social trust that facilitate coordination and cooperation for mutual benefit" ((Putnam 1995: 67 in (Krishna & Shrader, 2000)). Others regard trust more as an outcome of social capital (e.g. Woolcock, 1998). However, Woolcock, 1998 maintains that as such trust can still be used as an indicator to measure social capital. Regardless of the position one takes trust only captures an aspect of social capital.

Finally, not all scholars agree that trust is a good proxy for social capital. For example, Dasgupta, 2005 is a proponent of a more neutral definition of social capital and therefore proposes for social capital to be measured only by networks. The argument behind this is that social capital is not always able to "enhance human well-being" and it can also have detrimental effects (Dasgupta, 2005).

Despite the lack of consensus in the literature, trust has been used in a number of studies looking at the effects of social capital on a broad range of economic phenomena.

Self-reported general trust has been found to have a positive effect on economic growth (Knack & Keefer, 1997), on reduction in firearm violent crime (Kennedy, Kawachi, Prothrow-Stith, Lochner, & Gupta, 1998; Lederman, Loayza, & Menendez, 2002), on confidence in institutions (Brehm & Rahn, 1997), on the performance of large organizations and on the performance of the society more generally (health, education, infrastructure, GDP growth, inflation) (La Porta, Lopez-De-Silanes, Shleifer, & Vishny, 1996). In a developing country setting self-reported trust has been found to predict participation in rotating labour associations (Wang, 2009), repayment and saving levels of participants in a microcredit programme (Karlan, 2005) and energy adoption (Adrianzén, 2014; McEachern & Hanson, 2008).

Findings from behavioural economics and the social capital literature have been used to inform various strands of public policy to explain preferences, beliefs and choices and to offer policy fixes which increase welfare. This includes energy and development policy.

In a number of studies looking at technology adoption in developing countries, and energy efficiency investment decisions in developed countries, both market and behavioural failures as well as peer effects have been used to explain a number of phenomena. Namely the inability of individuals to make the adoption decision, to meet the required repayments and the non-optimal use of the technology after it has been acquired. Market failures refer to issues like liquidity constraints, credit constraints and information gaps. And behavioural failures to issues like time inconsistent preferences, computational difficulties and reference points. A range of policy recommendations have been suggested to address these underlying barriers e.g. price structures, subsidies, credit, social marketing, information campaigns, progressive tariffs, innovative financing solutions like mobile payments, microcredit and prepaid meters. (See (Foster & Rosenzweig, 2010; Gillingham & Palmer, 2013) for relevant reviews).

Although similar considerations have been suggested to apply in the case of electrification in developing countries (Bernard, 2010; Bonan et al., 2017) the issue, remains largely unexplored (Bonan et al., 2017). This thesis aims to address this gap by looking at how some of the demand-side barriers of electricity access can be informed by some findings of the behavioural economics and social capital literature. The focus of this thesis is on the adoption decision and on the payment patterns for electricity, in the case of solar hybrid mini-grids and isolated off-grid solar home systems.

Electrification access choices have some similarities with other technology adoption decisions, namely the high upfront costs often required, and the relevance of the social context including amongst others the role of peer effects on the decision to adopt a technology (positive and negative externalities as well as information and imitation effects). (Bonan et al., 2017)

Electrification access has however, its own unique characteristics in terms of the benefits of electrification, the costs structures, the type of externalities generated especially when the grid extension is involved (Bonan et al., 2017), as well as cognitive difficulties associated with the idiosyncrasies of energy consumption namely the difficulty to understand the billing methods and to calculate the consumption of energy consuming appliances (Bernard, 2010).

In addition, mini-grid and isolated off-grid solutions also differ compared to conventional centralized energy systems. As these off-grid systems rely on renewable sources of power they often provide more limited services to users and entail different requirements on the consumer side (e.g. maintenance responsibilities, demand-side management to enhance performance of the systems). In addition, as they are installed at the household or community level they are embedded in different social contexts compared to centralized grids

(Nieuwenhout et al., 2001; Nieuwenhout et al., 2000; Roland & Glania, 2011; Urmee, Harries, & Schlapfer, 2009).

Finally, the context of electricity consumption in developed countries has analogies with that in developing countries as individuals have to make similar choices regarding the purchase of electrical appliances and face similar difficulties to understand the billing methods and to manage their consumption. However, the two settings also differ in terms of the electrification rates, the availability of infrastructure, the quality of the service available and the socio-economic background of the users.

This exercise is therefore important to inform electrification access policy, but also to strengthen empirical findings from these other contexts.

2.2 Research objectives

This thesis aims to explore how some of the findings from the literature of behavioural economics and social capital can apply in the case of electricity access in developing countries with a focus on solar off-grid electrification. And specifically on solar home systems and solar hybrid mini-grid electrification projects in rural Guinea-Bissau.

Namely, I am drawing from studies looking at the role of discounting on technology adoption and recurring payments, the role of trust on technology adoption and the role of computational limitations and the use of simplification strategies on the accuracy of frequency and expenditure reporting in surveys.

Specifically, this thesis has the following research objectives:

- 1) Chapter 2 looks at the role of income limitations as well as of discount rates, hyperbolic discounting, that captures self-control problems, and self-reported levels of trust for different actors, on the demand for a solar home system and how these factors shape preferences for different different delivery models.
- 2) Chapter 3 examines the factors affecting the decision to connect to a community solar hybrid mini-grid with a focus on the role of trust for neighbours on the informal expansion of the grid infrastructure.
- 3) Chapter 4 tests if the use of different elicitation frames in surveys affects the accuracy of reported energy expenditures on surveys for clients of a solar hybrid

mini-grid using prepaid meters. The effect of the use of simplification strategies on response accuracy is also explored.

- 4) Chapter 5 looks at the how self-control problems and intra-household dynamics affect prepayment patterns for electricity for clients of a community solar hybrid mini-grid.

This exercise aims to inform electrification policy in developing countries, demonstrate instances where insights from behavioural economics and social capital can enrich our understanding of electrification policy in developing countries, but also demonstrate how these chosen case studies can help to strengthen empirical findings from other contexts.

This thesis is not an exhaustive account of how behavioural economics and the findings from the literature on social capital can inform access to electricity. It however delivers a novel contribution to knowledge by introducing a number of new applications that encompass the two main stages of electricity access: adoption decisions and usage decisions. Despite some piecemeal research into this field, to my knowledge, there does not appear to be an effort to create a more systematized study encompassing these different stages of the electrification process.

The following section discusses the relevant applications and the gaps in the literature. The thesis structure section that follows after, discusses how this thesis attempts to address these gaps and what is the contribution to knowledge.

3. Relevant gaps in the literature

Empirical evidence demonstrates that the adoption rates for welfare enhancing products that require high one-off investments that pay off over time are lower than expectations based on the rational model. This has been observed in developed countries in the case of energy efficiency investments (e.g. better insulation, fuel efficient vehicles, efficient appliances and lighting) also known as the “efficiency gap” or the “energy adoption” paradox (Jaffe & Stavins, 1994), but also in developing countries in the adoption of a number of products (fertilizers, health products) (Foster & Rosenzweig, 2010).

One explanation is that individuals have higher discount rates than assumed. Simply put individuals discount the future higher than theory expects, and therefore place a higher weight than expected on current compared to future costs and benefits. In many instances the observed purchases in the case of energy consuming durables have been used to calculate implicit discount rates which were found to be higher than market rates of return (Hausman, 1979; Train, 1985; Allcott & Taubinsky, 2013). This is done by looking at trade-offs between upfront purchase costs and the level of energy savings.

It is widely believed however, that a number of other factors, linked to market failures behavioural biases, or the social context could be driving this observed paradox.

A number of explanations from the standard economic model are the lack of information about benefits of available technology, hidden costs involved in the use of a new technology, energy price uncertainty (Jaffe & Stavins, 1994), principal agent problems (split incentives), which arise when the individual that makes the purchase decision is not the same as the individual that will pay the bills (Davis, 2011), low levels of consumption that render efficiency investments irrelevant (Morss, 1989), and the fact that other product features might be more important (Jaffe, Newell, & Stavins, 2004). Finally, income, liquidity and credit constraints can hinder the ability of individuals to meet the high upfront payments required (Golove & Eto, 1996). Liquidity and credit constraints have also been identified as main barriers of adoption of technology in developing countries. For example, Tarozzi et al., 2014 find that liquidity constraints inhibit the adoption of bed nets in India.

The explanations drawing from non-standard models of decision making range from the presence of time inconsistent preferences (hyperbolic discounting) that lead to self-control problems to the fact that such intertemporal choices are sensitive to other behavioural biases linked to bounded rationality as well as to the social context (Frederick, Loewenstein, & O'donoghue, 2002).

Hyperbolic discounting, bounded rationality and the social context are also relevant to explain other factors pertinent to technology adoption.

For example, hyperbolic discounting and the social context offer insights about the relative strengths of different billing methods. Findings from bounded rationality can inform the ways by which consumers calculate and report their energy expenditures more accurately. Finally, the role of the social context can be relevant to explain patterns of technology adoption also in instances where intertemporal trade-offs are not present.

All these applications are pertinent to electrification access in developing countries. The following section discusses relevant applications of hyperbolic discounting, bounded rationality and the role of the social context in more detail as well as the relevant gaps in the literature.

3.1 Hyperbolic discounting

Hyperbolic discounting is linked to bounded willpower. Hyperbolic discounting is the phenomenon whereby discount rates drop with higher time intervals, or are higher for trade-offs in the present than in the future. This has been confirmed in a number of experimental studies and captured in economic models (Ashraf, Karlan, & Yin, 2006; Camerer & Loewenstein, 2004; Laibson, 1997; Thaler, 1981).

More specifically hyperbolic discounting can be identified by comparing the fit of functional forms expressing declining discounting to those expressing constant discounting (Kirby, 1997; Myerson & Green, 1995). In addition, hyperbolic discounting can be identified experimentally where individuals are asked to make trade-offs between current and future gains or losses (usually monetary). In this case hyperbolic discounting is identified when individuals exhibit lower discount rates over longer time horizons than over short time horizons (e.g. Thaler, 1981) or when individuals have higher discount rates for more proximate trade-offs compared to trade-offs further in the future (e.g. Ashraf, Karlan, & Yin, 2006).

Hyperbolic discounting causes self-control problems or else procrastination. This is a situation whereby individuals keep putting-off actions which incur current costs even though these actions would make them better off from a welfare perspective in the future (Camerer & Loewenstein, 2004; Thaler & Shefrin, 1981).

The extent of this procrastination has been found to be affected by the awareness of problems of self-control (O'Donoghue & Rabin, 1999). More sophisticated individuals tend to have higher demand for commitment mechanisms that will help them address their self-control problems (Ariely & Wertenbroch, 2002; Ashraf et al., 2006).

For example, hyperbolic discounting has been shown to negatively affect an individual's ability to save (Ashraf et al., 2006; Bauer, Chytilová, & Morduch, 2012). Individuals with self-control problems have been found to have a higher demand for commitment devices such as saving (Ashraf et al., 2006) and credit schemes (Bauer et al., 2012; Dupas & Robinson, 2013). And access to such commitment devices has been found to increase the saving levels of these individuals (Dupas & Robinson, 2013).

Applications in developing countries have looked into the mechanisms of how self-control problems are hindering technology adoption, but also how different commitment mechanisms can help address these problems.

Through a randomized control trial Duflo, Kremer, & Robinson, 2011 find that self-control problems explain the low investments in fertilizers in Kenya, and that randomly allocated small discounts at the time of harvest allow farmers with hyperbolic preferences to commit to fertilizer use. Dupas & Robinson, 2013 find that hyperbolic discounting inhibits the ability of individuals to invest in health products in Kenya through affecting negatively their ability to save. They also find that access to a commitment device (credit with social commitment to make repayments) increases such investments (Dupas & Robinson, 2013).

Tarozzi, Mahajan, Yoong, & Blackburn, 2009 find that self-control problems limit the ability of households to treat their bed nets in India, but find no demand for commitment devices (a contract that includes two retreatments of the purchased bed net) for individuals with self-control problems (Tarozzi, Mahajan, Yoong, & Blackburn, 2009).

Applications on energy purchase decisions are very limited. Hyperbolic discounting might induce individuals to put-off welfare enhancing purchases related to energy efficiency (Gillingham & Palmer, 2013; Heutel, 2015). These effects can also be indirect through affecting one's inability to save to meet the upfront payments required. Bradford, Courtemanche, Heutel, McAlvanah, & Ruhm, 2014 undertake the only study, to my knowledge, that tests this assumption on self-reported energy efficiency actions in a developed country context and find a positive correlation between hyperbolic discounting and the low use of a number of energy-efficient products (high fuel economy vehicles, home insulation), but not for other (efficient lighting). However, it is not clear if these effects are direct or indirect.

So far studies have not looked at how these issues may apply in the case of electrification decisions in developing countries in general and demand for solar home systems in particular, despite the fact that often these decisions include large upfront costs that only pay off, over time. In addition, despite substantial work done on the role of different commitment mechanism to limit the negative effect of hyperbolic preferences, the interaction of self-control problems with a preference for credit and rental schemes, in the context of solar home system demand, hasn't been tested. Such an exercise would help explain more in detail the relevant strengths of these different delivery models for solar home systems.

Chapter 2 of this thesis undertakes a stated preference study using a hypothetical choice experiment to estimate demand for different delivery models of a solar home system including upfront, credit and rental schemes in Guinea-Bissau. This chapter addresses this gap as it investigates, amongst other things, the role of hyperbolic preferences on delivery model preference.

Apart from affecting an individual's ability to meet the high upfront costs often required for technology adoption self-control problems can also have direct negative implications on the consumers' ability to meet recurring expenditures required by billing systems. Through their negative effect on saving self-control problems might hinder the ability of consumers to meet their monthly electricity payments. In addition, individuals with self-control problems could have a harder time saving electricity at home (Brutscher, 2011). More flexible payment methods (e.g. the use of prepaid meters, where consumers pay for the electricity they consume in advance and they are allowed to choose the size and timing of the payment and to consume accordingly) allow to address income and liquidity constraints but also self-control problems, as individuals can use smaller refill levels as commitment mechanism to use less electricity at home (Brutscher, 2011). However, since self-control problems affect individuals' ability to save and smooth their income this might lead to a reduction of electricity use during the months of lower revenues (this is especially relevant in developing countries when income is highly seasonal) and increase the occurrence of self-disconnection (Brutscher, 2012a, 2012b). Very little empirical research exists in this domain.

The only exception is Brutscher, 2012b that studies the drivers of self-disconnection for customers using prepayment for electricity in the case of Great Britain. However, this study only looks at the effect of self-control problems (elicited through time preference measures) on the seasonality of self-disconnection, which is found to be positive. In another study looking at prepayment patterns for customers using prepayment for electricity in Northern Ireland Brutscher, 2011 does not attempt to elicit hyperbolic preferences in order to test how they

might be affecting prepayment patterns. In addition, no work has been done to test the effects of hyperbolic preferences on prepayment patterns in a developing country setting.

Chapter 5 of this thesis addresses this gap as, amongst other issues, it looks at the role of self-control problems in driving prepayment patterns for electricity in a developing country setting. This chapter combines actual information on the prepayment of clients of a solar hybrid mini-grid operating in Guinea-Bissau, and time preference measures elicited through a survey.

3.2 Bounded rationality

Congdon et al., 2011 classify all biases that lead to bounded rationality (outside the ones emanating from prospect theory discussed below) in three broad categories: limited attention, limited computational capacity, and biased reasoning. These “have broadly similar consequences ... leading individuals to make decisions based on heuristics and biases ... shortcuts or crude rules of thumb that can be incorrect”.

The human brain does not have the capacity to factor in all aspects of a choice, this phenomenon is known as limited attention, and it leads to salience effects whereby decisions are influenced by those features of the choice made noticeable (Kahneman, 1973; Pashler, Johnston, & Ruthruff, 2001). Computational limitations on the other hand refer to incorrect processing of the relevant alternatives even if all aspects of a choice are taken into consideration. This includes common practices of individuals like inability to make choices when there are too many alternatives (choice overload) (Iyengar & Lepper, 2000; Tversky & Shafir, 1992), inability to process complex prices schedules properly (average vs marginal prices) (Lieberman, 2004), the projection of one’s current situation and preferences into the future (projection bias) (O'Donoghue & Rabin, 1999) and grouping expenditures in different budget categories and assigning them to accounts with a different propensity to consume (mental accounting) (Thaler, 1999).

Finally, there are a few systematic biases emanating from “the way that the human brain processes probabilities”. In their seminal work Tversky & Kahneman, 1975 find that in order to evaluate probabilities individuals rely on heuristic principles used to simplify complex tasks, which can be useful but can also lead to systematic errors. More specifically individuals assess probabilities of occurrence of events according to how representative they are (representativeness heuristic), they use instances that come in mind to assess frequencies

(availability heuristic) and anchor their assessments based on information available or incomplete computation (adjustment and anchoring) (Tversky & Kahneman, 1975). The model since then has been extended to apply on other decision environments and not just decision making under uncertainty (Kahneman, 2003; Kahneman & Frederick, 2002).

Bounded rationality explains partly the efficiency gap as consumers tend to make computational errors that place more weight on upfront purchase costs in comparison to recurring expenditures.

Evidence suggests that consumers behave consistently with bounded rationality when it comes to making decision about energy in developed countries. In an experiment Allcott & Taubinsky, 2013 demonstrate that individuals pay less attention on recurring costs when they purchase lamps online as information provision on costs increases demand for efficient light bulbs (but not at the store) (Allcott & Taubinsky, 2013) and survey evidence shows that consumers pay less attention on fuel costs when they purchase cars (Allcott, 2011). Similarly, through survey evidence it is demonstrated that consumers also fail to understand the curvilinear relationship between miles per gallon (MPG) and fuel efficiency, and therefore undervalue the benefits from removing highly inefficient cars (Allcott, 2013; Larrick & Soll, 2008).

When consumers assess their car fuel expenditures they make these calculations based on current prices as revealed by semi-structured interviews (Turrentine & Kurani, 2007) and quantitative survey research (Allcott, 2011; Anderson, Kellogg, & Sallee, 2013). The same holds in the case of residential energy, as shown by a study based on semi-structured interviews (Kempton & Montgomery, 1982). Similarly, Ito, 2014 uses observational data to show that consumers respond to average rather than marginal electricity prices.

Reference dependent preferences and loss aversion are main features of the prospect theory created to address limitations of expected utility theory for decision making under risk, but it is also extended for riskless decision (Kahneman & Tversky, 1979, 1984; Tversky & Kahneman, 1991). In the presence of reference dependent preferences utility is not purely based on final wealth states, but it is dependent on a reference which could be the status quo, expectations and social comparisons. Loss aversion refers to the situation whereby individuals value losses more than equivalent gains. Some implications of loss aversion are the endowment effect, which is the observation that individuals value more things that they already possess (Kahneman, Knetsch, & Thaler, 1990; Thaler, 1980), and status quo bias that maintains that individuals prefer to stick to the status quo (Samuelson & Zeckhauser, 1988). Two main implications of these findings for policy are the role of defaults and framing. Individuals tend

to choose the default options and react more strongly to options framed in terms of losses than to options framed in terms of gains (Kahneman & Tversky, 1984; Madrian & Shea, 2001).

Reference dependence and loss aversion are expected to have direct implications on decisions to invest on energy efficiency as they affect the way consumers perceive upfront in relation to recurring costs. In addition, these findings present room for policy interventions through the role of framing and the use of defaults. However, empirical research so far is scant (Gerarden, Newell, & Stavins, 2015; Greene, Evans, & Hiestand, 2013). One exception is the study undertaken by Dinner, Johnson, Goldstein, & Liu, 2011, which presents experimental evidence that replacing incandescent light bulbs with CFLs as the default significantly increased the proportion of subjects who chose CFLs.

The above findings have established the role of bounded rationality in the efficiency gap. One of the main challenges is isolating the effect of bounded rationality from competing explanations, which remains empirically difficult especially in observational studies (see Geraden, Newell & Stavins, 2015; Gillingham, Palmer, 2013). In addition, to my knowledge, no work has been done to see how bounded rationality issues affect the way by which individuals process information regarding energy expenditures in developing countries and the subsequent negative effects this might have on electrification and energy access in general.

Applications from bounded rationality do not only have the potential to inform the energy efficiency gap (and technology adoption paradox in general), but also survey methodology. Heuristic decision making has been found to be present when individuals report frequency of behaviour and expenditure in surveys. For example, by combining survey reporting with direct response strategy elicitation (where respondents are asked to explain the way they form their responses), research has shown that respondents often use simplification strategies to report the frequency of certain behaviour. These simplification strategies can be based on information available in memory, but also on contextual information (i.e. the survey instrument) (Menon, 1993; Menon, Raghbir, & Schwarz, 1995). There is still however, no consensus on whether the use of these simplification strategies lead to more or less accurate reporting (Tourangeau, Rips, & Rasinski, 2000).

No such application has been undertaken for energy expenditure reporting in developing countries. Such an exercise is warranted to shed light on the level of accuracy and the potential biases of energy expenditure surveys and how they can be made more accurate. This is important in order to be able to collect more accurate data in energy expenditure surveys that are often used to inform policies especially in developing countries.

Chapter 4 of this thesis addresses this gap as it compares real energy expenditure data

on prepayment, from a solar hybrid mini-grid operating in the semi-urban community of Bambadinca in Guinea-Bissau, with survey elicited energy expenditure data to test the accuracy of survey responses on energy expenditure and how this accuracy can be improved with the use of different recall periods, namely a ‘usual’ week versus a ‘specific’ (i.e. last) week. This chapter also assesses the the accuracy of the different response strategies used.

3.3 The role of social capital and trust on technology adoption

Despite the limitations mentioned, this thesis uses trust as a partial measure of social capital. There are a number of mechanism through which trust as a measure of social capital could be influencing technology adoption decisions.

As Narayan & Pritchett, 1999 discuss, on the one hand social capital can enable the diffusion process. At the same time social capital may increase cooperation, reduce transaction costs and enhance enforcement which can increase collective action. Finally, social capital could lead to increased “risk sharing among individuals and act as an informal safety net” (Narayan & Pritchett, 1999).

In the case of the diffusion process Manski, 2000 identifies three channels through which social interactions affect economic decisions that have been proven to be relevant for technology adoption. The first channel is through constraint interactions, where an individual’s economic decision entails externalities (positive or negative) and therefore affects the economic decisions of others. In the case of technology adoption these constraint interactions can take the form of cost reductions for late adopters or the indirect use of the benefits of the technology from non-adopters. The second channel is through expectation interactions, where an individual’s economic decision affects the knowledge of others. In the case of technology adoption this takes the form of social learning about new technologies. And finally, the third channel is through preference interactions where one’s economic decision affects the preferences of other individuals. In the case of technology adoption this is expressed as imitation effects (Bernard & Torero, 2015; Manski, 2000).

“Depending on their size, social interaction effects may contribute to high or low adoption equilibrium of particular commodities, technologies, or behaviour” (Bernard & Torero, 2015). These social interaction effects can inform the efficiency gap, but also technology adoption decisions in general.

Although a number of applications in developing countries have looked at the role of peer effects on technology adoption the focus has mostly been placed on expectation interactions and preference interactions. These applications are mainly on agriculture (Bandiera & Rasul, 2006; Conley & Udry, 2010; Isham, 2002), but there are also studies on health (Kremer & Miguel, 2007), water (Devoto, Duflo, Dupas, Parienté, & Pons, 2012), electrification (Barron & Torero, 2015; Bernard & Torero, 2015) and cookstove adoption (Adrianzén, 2014). These studies use different methods to isolate the role of peer effects some measure the types and sizes of relevant networks of individuals (e.g. Bandiera & Rasul, 2006), others use self-reported trust measures (Adrianzén, 2014) and others vary the level of adopters exogenously (e.g. (Barron & Torero, 2015; Bernard & Torero, 2015 through the random provision of subsidies)).

Most studies attribute the presence of peer effects to learning or imitation effects, by rejecting other potential channels through observations, the use of secondary data and result interpretation (Bandiera & Rasul, 2006; Bernard & Torero, 2015). Constraint interactions have been studied less, but are however very relevant for electrification especially for technologies involving grid infrastructure.

The ability of social capital to enhance collective action has been an argument in favour of community driven development. Empirical evidence has however, highlighted that when such projects are implemented potential divisions within the community could lead to elite capture and have negative effects for marginalized groups (Mansuri & Rao, 2004). There hasn't been a study looking at how potential divisions within a community can negatively affect electrification projects undertaken at the community level.

Mini-grids present a good case study to address these gaps as they operate at the community level and involve a range of dynamics relevant to the community driven literature and the study of peer effects.

Chapter 3 looks at how trust amongst neighbours can increase connections, to a solar hybrid mini-grid installed in the semi-urban community of Bambadinca in Guinea-Bissau, through enabling the informal expansion of the grid, which is a type of constraint interactions. This study also looks at the potential of divisions within the community to negatively affect connections.

Finally, the ability of social capital to increase “risk sharing among individuals and act as an informal safety net” (Narayan & Pritchett, 1999) has been linked with both positive and negative outcomes that can be associated with technology adoption. For example, Karlan, 2005

finds that self-reported trust can predict loan repayments. However, at times some intra-household dynamics could have negative effects.

For example, Dupas & Robinson, 2013 suggest that social pressures to share money can be a strong factor limiting one's inability to save to make health investments. Earmarked saving devices are shown to deal with social pressures to share money (Dupas & Robinson, 2013). Brutcher, 2012a finds a similar negative effect of social pressures to share money on individuals' ability to save to purchase heating oil, and finds that heat stamps help increase saving through limiting social pressures and not because they address self-control problems.

No study has yet looked at how trust for different actors, and social pressures to share money can affect the preference for different delivery models for solar home systems. In addition, no study has looked yet at how social pressures to share money through their negative effect on saving can affect consumption patterns in the case prepayment for electrification in a developing country setting.

Chapter 2 of this thesis also examines the role of trust for different actors on delivery model preference for solar home systems and Chapter 5 investigates the role of intra-household dynamics, including pressures to share money, on prepayment for electricity.

4. Thesis structure

This thesis addresses a number of the gaps in the literature mentioned above in the following chapters:

Chapter 2 presents the results of a stated preference study that uses a hypothetical choice experiment to estimate willingness to pay for a solar home system for different delivery models within the region of Bafatá in Guinea-Bissau. These different delivery models (upfront, rental and credit scheme) include trade-offs between upfront and recurring costs with different time frames and different maintenance responsibilities. Importantly the study looks at the potential role of income constraints, discount rates, hyperbolic preferences, and trust for different actors (measured through survey questions) on these choices. Results suggest that rental schemes capture the largest market share in comparison to upfront payment and credit schemes. Preferences are driven by income factors. In addition, there is some evidence that individuals with self-control problems have a preference for credit schemes, and high discount rates are linked with lower demand for upfront and credit schemes. Finally, low levels of trust

for actors in the community are associated with a lower preference for credit and rental schemes.

This indicates that the different repayment schemes address not only income limitations but also self-control problems, excessive discounting and limitations relevant to the social context. This study contributes to the literature examining the drivers and barriers of technology adoption where intertemporal trade-offs are present, as it is the first to attempt to control for the effect of hyperbolic discounting, high discount rates and trust in the decision to adopt a SHS and the associated delivery model choice. The controlled nature of the choice experiment also allows to rule out some of the alternative explanations (e.g. computational limitations as respondents are informed about the total costs of the different options).

This study also contributes to the literature of solar home system adoption as it is the first study to use a hypothetical choice experiment to study the preferences for different delivery models of solar home systems and their underlying determinants.

Chapter 3 studies the factors that drive the decision to connect to a solar hybrid mini-grid installed in the semi-urban community of Bambadinca in Guinea-Bissau with a focus on the role of social capital, as expressed in self-reported trust for one's neighbours, in facilitating electricity connections through the informal expansion of the grid. The informal expansion of the grid, is a process whereby neighbours come into agreements on how to share each other's connecting infrastructure and the associated costs. This can have significant cost reductions and is seen as a form of constraint interactions. Trust for one's neighbour is expected to play a positive role in the process of the informal expansion of the grid as it can enhance the ability of neighbours to reach such agreements. I attempt to isolate the effect of trust on the informal expansion of the grid as, unlike other peer effects, it only becomes relevant for households that are farther away from the main grid. This study combines actual observations of the connection decision with responses to a baseline survey containing information on the socio-economic status of the households and self-reported trust about different actors in the community. Findings show some evidence that social capital as expressed with trust for one's neighbours', has a positive effect on electricity connections through the informal expansion of the grid.

Results also suggest that connections are driven by a number of standard socio-economic factors suggested by the electrification and technology adoption literature (e.g. income, upfront connection costs and prior possession of appliances). Social capital as expressed with trust for a number of actors in the community and variables reflecting a households' integration in the community are not found to be affecting the connection decision.

This is the first study to look at the role of trust on constraint interactions (achieved

through the informal expansion of the grid) as well as the first study to look at the potentially negative effects of community divisions in the context of rural electrification. This study also contributes to the literature of community mini-grids by looking at the the determinants of electrification.

Chapter 4 explores how the technology of prepaid meters can help researchers acquire more insight on the accuracy of survey expenditure reporting and the response strategies used. More specifically, this chapter tests the accuracy of reported energy expenditure in surveys, when using differently defined recall periods, namely a ‘usual’ week versus a ‘specific’ (i.e. last) week. Real expenditure data for prepaid meters for energy, from a solar hybrid mini-grid operating in the semi-urban community of Bambadinca in Guinea-Bissau, are compared with answers from a survey where respondents are asked to answer randomly in different recall periods. Overall, our results show that respondents tend to over-report the level and frequency of their energy expenditures, but reporting is more accurate when the ‘specific’ period rather than when the ‘usual’ period is used. Expenditure specific characteristics have a stronger effect on the level of misreporting than individual and household specific characteristics. The level of average weekly expenditure, as well as the irregularity of weekly repayment frequency, retain a robust effect on all the different measures of error used. In addition, the effect of the irregularity of weekly repayment frequency is more pronounced when the ‘specific’ period is used, which is attributed to the use of different response strategies and their varying effects on accuracy. However, this last finding is only robust for frequency reporting and not for expenditure level reporting.

This is the first study to corroborate the accuracy of different recall periods with real data, in the context of energy expenditure in developing countries.

Apart from its contribution to survey methodology this chapter contributes to the strand of literature looking at how individuals assess their energy expenditures and the role of computational limitations. No other study has looked before at the role of response strategies used on accuracy of energy expenditure reporting. Finally, this exercise suggests that energy expenditures can be a useful case study for the study of expenditure reporting related biases as information on actual energy expenditures is becoming increasingly available.

Chapter 5 investigates the factors affecting prepayment patterns for electricity with a focus on the role of self-control problems and intra-household dynamics. This is for clients of a solar hybrid mini-grid installed in the semi-urban community of Bambadinca in Guinea-Bissau. This study uses the actual prepayment information of the clients coupled with survey measures which also include measures of time preference. Results indicate that overall there is

a preference for small and frequent repayments. The level of monthly expenditure is driven positively, amongst other factors, by income levels and using the service for income generating activities. Self-control problems affect negatively the level of refill amounts indicating that customers with self-control problems use smaller refill amounts as a method to commit to using less electricity at home. Similarly, individuals charged an additional higher tariff for their consumption between 7pm to 12am choose smaller refill amounts, from those that are not, possibly as a method to control their electricity consumption patterns. The effect of seasonality of income on expenditure levels, self-disconnection, and using electricity at times when it is most expensive to consume is not found to be driven by self-control problems or intra-household dynamics. This is the first study to investigate these issues in the context of a developing country setting.

Chapter 6 provides concluding remarks.

5. Methods and limitations

Lab experiments, and field experiments often used by behavioural economists allow to isolate the measurements of interest from confounding effects by creating counterfactuals through randomization.

In natural or framed field experiments the experiment is undertaken in an actual field context in respect to the commodity, the behaviour and the incentives in question as well as external factors like the information available. This improves generalizability in comparison to lab experiments and artefactual field experiments (lab experiment choosing a subject pool from the population of interest relevant to the field context) where participants are asked to participate in tasks with a given set of rules and abstract framing. (Harrison & List, 2004)

Natural experiments differ from framed field experiments as in the latter subjects are aware of their participation to experiments. Therefore, natural field experiments allow to eliminate experimenter effects and selection bias (Harrison & List, 2004). Conducting a natural or framed field experiment to measure the demand for a solar home system and the respective characteristics of the delivery models in Chapter 2 instead of a hypothetical choice experiment would have allowed to minimise hypothetical bias as well as other biases linked with stated preference methods (Mitchell & Carson, 1989) (discussed more in detail in Chapter 2) However, it was not possible to undertake such an endeavour given the limited means and time frame of this study. In addition, the logistics required were not available. The product did not exist yet and there was no structure in place to offer it with varying attributes to the consumer base. The hypothetical choice experiment method was chosen as it allows to conduct valuations in the absence of an actual market and to have control over the attributes of the product under valuation (Mitchel and Carson, 1989).

Similarly, incentivized lab experiments are often used to measure time preferences. Time preference measures were not incentivised in this thesis mainly due to logistical issues. The inclusion of a time preference reversal component, to identify self-control problems, would have required to return to the communities a year latter to make the payment according to choice, which was not possible. The potential implications of this choice are discussed more in detail in Chapters 2 and 5.

Finally, for all the surveys undertaken respondents were not compensated for their time as in discussion with local stakeholders it was suggested that compensation for participation in surveys and focus groups was not common practice and it could potentially cause disruptive dynamics in the community. Namely between households that were chosen to participate and

those that weren't. In addition, compensation could cause a precedent and impact negatively future work within the community as project implementation often requires frequent focus group studies, interviews and baseline studies. Whittington, 2004 discusses an additional negative effect of compensating survey participants in developing countries. As participation in such surveys should be voluntary Whittington, 2004 argues that in environments of extreme poverty it is hard to argue that even minimal compensation does not have a coercive character.

6. Case study - Research location

This thesis is an outcome of collaboration with TESE- Development Association, a Portuguese non-governmental organization (NGO) working on infrastructural projects in Guinea-Bissau. This thesis is based on two case studies which are both projects of TESE- Development Association. The first project is a solar hybrid mini-grid, currently operating in Bambadinca (a semi-urban community situated in the Bafatá region) (see Chapter 3 for more details). The second project has not yet been implemented but aims to service the region of Bafatá in Guinea-Bissau with a range of solar home system products and delivery models that the consumer can choose from (see Chapter 2 for more details).

This thesis is based on case studies from the Bafatá region of Guinea-Bissau. Guinea-Bissau is a country located in the western coast of Africa bordering the North Atlantic Ocean, between Guinea and Senegal. The country has a land-mass of approximately 36,125 sq km, 52% of which is covered by forest, and a 350 km of coastline giving way to the Archipelago of Bijagos (see Figure 3) (CIA World Factbook).

Guinea-Bissau is a former Portuguese colony, which achieved its independence in 1974. A mosaic of ethnic groups, languages and religions, according to the latest census (RGPH, 2009) Guinea-Bissau has a population of 1.45 million with the majority leading a rural life (subsistence farmers, fishermen (ILAP II, 2010)). Guinea-Bissau is one of the poorest countries in the world with its economy heavily reliant on subsistence agriculture and cashew nut exports. In its recent history the country has experienced violent conflict and unstable governments (IMF, 2011).

The country's human development index (HDI) ranking 178 out of 188 countries, reflects the social and economic problems it is confronting, along with its weak institutions. Most households do not have access to safe water; sanitation facilities and medical care (IMF,

2011) and 69.3% of Bissau-Guineans remain below the national poverty line (Human Development Report, 2015). Life expectancy at birth is 55.2 and the literacy rate is 56.7% (Human Development Report, 2015).

Generally basic infrastructure is lacking with electrification rates being very low. According to the World Energy Outlook energy access database, in 2013 the national electrification rate in Guinea-Bissau was 21% and the rural electrification rate 6% in addition, 98% of the population relied on the traditional use of biomass.

Electricity, water production and distribution in Guinea-Bissau has collapsed since 2000, after a catastrophic civil war left the country bankrupt and unable to finance a power supply entirely dependent on petroleum. Power production capacity declined from 20 MW in 2000 to a current 5.5 MW (IMF, 2011).

Guinea-Bissau has an average solar irradiation of 5.8 kWh/m²/day. This very promising potential for the development of solar energy however remains largely unexploited. Nevertheless, the number of projects and finance in the sector of solar energy are increasing and there is a preference for solar energy for lighting and water pumping, compared to other renewable options (SNV, 2011).

The region of Bafatá, is one of the nine administrative divisions of Guinea-Bissau³ (see Figure 1) and is located in North-Central Guinea-Bissau. The capital of the region, Bafatá city, is the third largest city of the country. Bafatá is divided into 6 sectors⁴. 15,5% of the Bissau-Guinean population lives in the region of Bafatá, 75,5 % of which lives below the level of poverty (ILAP II, 2010). A power plant, operating from the city of Bafatá and extending throughout the region until early 2000, currently operates sporadically and only within the city limits. The population is largely dependent on traditional energy sources (e.g. candles, flashlights), or highly polluting inefficient power generating alternatives that the majority cannot afford (e.g. private generators).

The socio-economic and energy access status as well as its potential for solar energy development render Guinea-Bissau very relevant for the study of access to electrification and solar energy applications.

Despite the inevitable case specific idiosyncrasies, findings are expected to be generalizable on a large extent to rural settings of other developing countries facing similar circumstances i.e. low HDI levels, similar social and economic problems, low electrification

³ Bafatá, Biombo, Bissau, Bolama/Bijagos, Cacheu, Gabu, Oio, Quinara, Tombali

⁴ Bafatá, Bambadinca, Contuboel, Galomaro, Gamamundo, Xitole

rates and absent grid infrastructure, but a promising potential for the development of solar energy. Such countries include especially other countries in Western Africa like Guinea, Liberia, Mali and Sierra Leone.

In addition, although the focus of this thesis is on off-grid solar applications some of the findings can be generalizable to other technologies. For example, the use of prepaid meters and the role of trust in the expansion of the grid infrastructure can also apply to centralized grid applications.

Finally, the study of electrification access in Guinea-Bissau presents an additional opportunity to gain insights from a Sub-Saharan African country, that has overall been very little exposed to research and does not attract much global attention. Indicative is the fact that a simple search in the EconLit database with the key word ‘Guinea-Bissau’ renders only 73 results. This pales in comparison to results given for other countries in the continent like Ghana (3,168), Ethiopia (1,964) Nigeria (4,287) and Kenya (3,515), but even for neighbouring Western African countries that also attract less research attention Mali (656), Senegal (821), Guinea (962), Liberia (229) and Gambia (212)⁵.

⁵ Search conducted in 15/06/2017

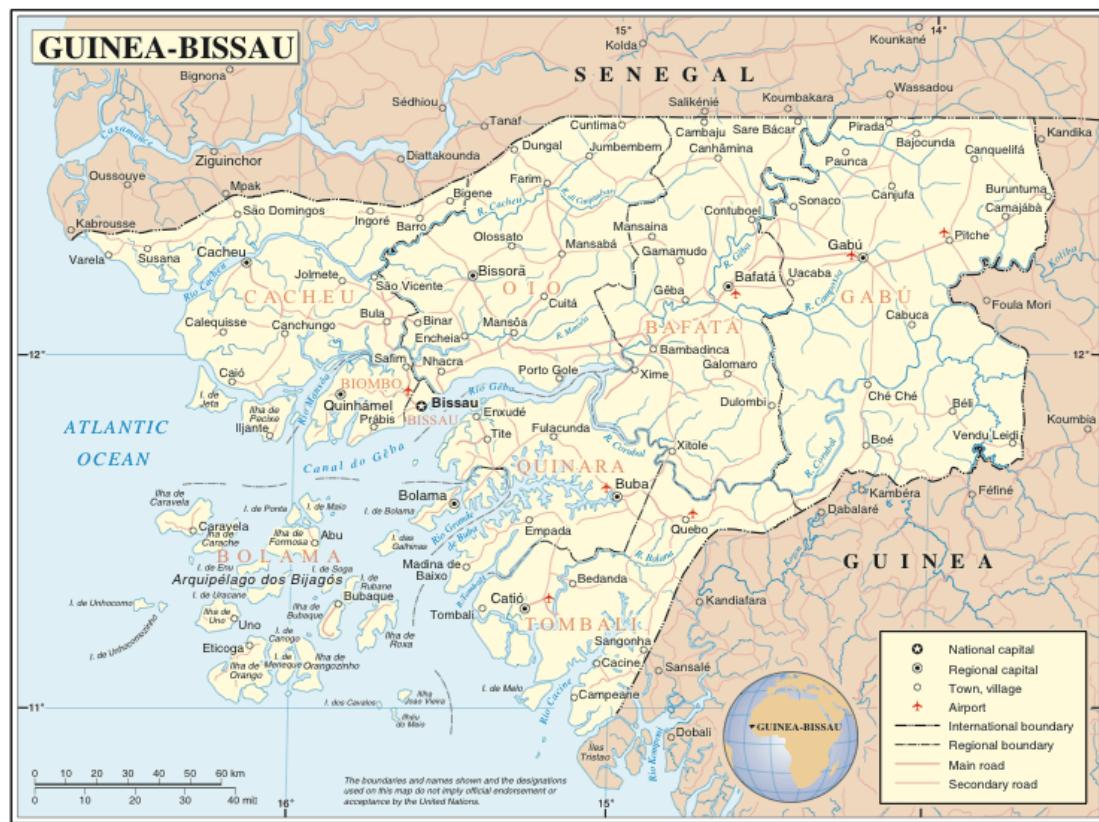


FIGURE 1 MAP OF GUINEA-BISSAU⁶

⁶ UNITED NATIONS Department of Field Support Cartographic Section, 2012

7. References

Adrianzén, M. A. (2014). Social capital and improved stoves usage decisions in the Northern Peruvian Andes. *World Development*, 54, 1-17.

Allcott, H. (2011). Consumers' perceptions and misperceptions of energy costs. *The American economic review*, 101(3), 98-104.

Allcott, H. (2013). The welfare effects of misperceived product costs: Data and calibrations from the automobile market. *American Economic Journal: Economic Policy*, 5(3), 30-66.

Allcott, H., & Taubinsky, D. (2013). The lightbulb paradox: Evidence from two randomized experiments. *National Bureau of Economic Research*.

Anderson, S. T., Kellogg, R., & Sallee, J. M. (2013). What do consumers believe about future gasoline prices? *Journal of Environmental Economics and Management*, 66(3), 383-403.

Ariely, D., & Wertenbroch, K. (2002). Procrastination, deadlines, and performance: Self-control by precommitment. *Psychological science*, 13(3), 219-224.

Ashraf, N., Karlan, D., & Yin, W. (2006). "Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines." *The Quarterly Journal of Economics* 121.2 (2006): 635-672. *The Quarterly Journal of Economics*.

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in northern Mozambique. *The Economic Journal*, 116(514), 869-902.

Barron, M., & Torero, M. (2015). Fixed Costs, Spillovers, and Adoption of Electric Connections.

Bauer, M., Chytilová, J., & Morduch, J. (2012). Behavioral foundations of microcredit: Experimental and survey evidence from rural India. *The American economic review*, 102(2), 1118-1139.

Bernard, T. (2010). Impact analysis of rural electrification projects in sub-Saharan Africa. *The World Bank Research Observer*, 27(1), 33-51.

Bernard, T., & Torero, M. (2015). Social interaction effects and connection to electricity: Experimental evidence from Rural Ethiopia. *Economic Development and Cultural Change*, 63(3), 459-484.

Bonan, J., Pareglio, S., & Tavoni, M. (2017). Access to modern energy: a review of barriers, drivers and impacts. *Environment and Development Economics*, 1-26.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., & Ruhm, C. (2014). Time preferences and consumer behavior. *National Bureau of Economic Research*.

Brehm, J., & Rahn, W. (1997). Individual-level evidence for the causes and consequences of social capital. *American journal of political science*, 999-1023.

Brutscher, P.-B. (2011). Payment Matters?-An Exploratory Study into the Pre-Payment Electricity Metering.

Brutscher, P.-B. (2012a). Making Sense of Oil Stamp Saving Schemes.

Brutscher, P.-B. (2012b). Self-Disconnection Among Pre-Payment Customers-A Behavioural Analysis.

Camerer, C., & Loewenstein, G. (2004). Behavioral Economics: Past, Present, and Future *Advances in Behavioral Economics*. Colin F. Camerer, George Loewenstein and Matthew Rabin, eds. Princeton: Princeton University Press.

CIA World Factbook. <https://www.cia.gov/library/publications/the-world-factbook/>. Retrieved 17/6/2015

Congdon, W. J., Kling, J. R., & Mullainathan, S. (2011). *Policy and choice: Public finance through the lens of behavioral economics*: Brookings Institution Press.

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *The American economic review*, 100(1), 35-69.

Dasgupta, P. (2005). Economics of social capital. *Economic Record*, 81(s1).

Davis, L. W. (2011). Evaluating the slow adoption of energy efficient investments: are renters less likely to have energy efficient appliances? In *The design and implementation of US climate policy* (pp. 301-316): University of Chicago Press.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature* 47 (2): 315-372.

Devoto, F., Duflo, E., Dupas, P., Parienté, W., & Pons, V. (2012). Happiness on tap: Piped water adoption in urban Morocco. *American Economic Journal: Economic Policy*, 4(4), 68-99.

Dinner, I., Johnson, E. J., Goldstein, D. G., & Liu, K. (2011). Partitioning default effects: why people choose not to choose. *Journal of Experimental Psychology: Applied*, 17(4), 332.

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *The American economic review*, 101(6), 2350-2390.

Dupas, P., & Robinson, J. (2013). Why don't the poor save more? Evidence from health savings experiments. *The American economic review*, 103(4), 1138-1171.

Durlauf, S., & Fafchamps, M. (2005). "Social Capital," in Aghion, Philippe and Steven N. Durlauf (eds.), *Handbook of Economic Growth*, 1B, (2005), Amsterdam, Elsevier, 1639-1699.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annu. Rev. Econ.*, 2(1), 395-424.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2), 351-401.

Gerarden, T. D., Newell, R. G., & Stavins, R. N. (2015). Assessing the energy-efficiency gap. *National Bureau of Economic Research*. Gillingham, K., Newell, R. G., & Palmer, K. (2009). Energy efficiency economics and policy. *Annu. Rev. Resour. Econ.*, 1(1), 597-620.

Gillingham, K., & Palmer, K. (2013). Bridging the energy efficiency gap: Insights for policy from economic theory and empirical analysis.

Golove, W. H., & Eto, J. H. (1996). Market barriers to energy efficiency: a critical reappraisal of the rationale for public policies to promote energy efficiency. *LBL-38059*. Berkeley, CA: Lawrence Berkeley National Laboratory.

Greene, D. L., Evans, D. H., & Hiestand, J. (2013). Survey evidence on the willingness of US consumers to pay for automotive fuel economy. *Energy Policy*, 61, 1539-1550.

Grimm, M., Munyehirwe, A., Peters, J., & Sievert, M. (2016). A first step up the energy ladder? Low cost solar kits and household's welfare in rural Rwanda. *The World Bank Economic Review*, lhw052.

Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of economic literature*, 42(4), 1009-1055.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 33-54.

Heutel, G. (2015). Optimal policy instruments for externality-producing durable goods under present bias. *Journal of Environmental Economics and Management*, 72, 54-70.

Human Development Report. (2015). Work for Human Development. United Nations Development Program.

ILAP II. (2010). Rapid Poverty Assessment Survey in Guinea Bissau. Ministry of Finance and Economics

IMF. (2011). Guinea-Bissau: Second Poverty Reduction Strategy Paper. Country Report No. 11/353.

Isham, J. (2002). The effect of social capital on fertiliser adoption: Evidence from rural Tanzania. *Journal of African Economies*, 11(1), 39-60.

Ito, K. (2014). Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. *The American economic review*, 104(2), 537-563.

Iyengar, S. S., & Lepper, M. R. (2000). When choice is demotivating: Can one desire too much of a good thing? *Journal of personality and social psychology*, 79(6), 995.

Jack, B. K., & Smith, G. (2015). Pay as You Go: Prepaid Metering and Electricity Expenditures in South Africa. *The American economic review*, 105(5), 237-241.

Jaffe A, Newell R, & Stavins R. (2004). The Economics of Energy Efficiency. . In *Encyclopedia of Energy*, ed. C Cleveland, pp. 79–90. Amsterdam: Elsevier.

Jaffe, A. B., & Stavins, R. N. (1994). The energy paradox and the diffusion of conservation technology. *Resource and Energy Economics*, 16(2), 91-122.

Jordan, M., Corry, J., & Jaques, I. (2017). Energy Efficiency: A Key Enabler for Energy Access. *International Bank for Reconstruction and Development/The World Bank*.

Kahneman, D. (1973). *Attention and effort* (Vol. 1063): Prentice-Hall Englewood Cliffs, NJ.

Kahneman, D. (2003). A perspective on judgment and choice: mapping bounded rationality. *American psychologist*, 58(9), 697.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment*, 49, 49-81.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental tests of the endowment effect and the Coase theorem. *Journal of Political economy*, 98(6), 1325-1348.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: Journal of the econometric society*, 263-291.

Kahneman, D., & Tversky, A. (1984). Choices, values, and frames. *American psychologist*, 39(4), 341.

Karlan, D. S. (2005). Using experimental economics to measure social capital and predict financial decisions. *American Economic Review*, 95(5), 1688-1699.

Kempton, W., & Montgomery, L. (1982). Folk quantification of energy. *Energy*, 7(10), 817-827.

Kennedy, B. P., Kawachi, I., Prothrow-Stith, D., Lochner, K., & Gupta, V. (1998). Social capital, income inequality, and firearm violent crime. *Social science & medicine*, 47(1), 7-17.

Kirby, K. N. (1997). Bidding on the future: Evidence against normative discounting of delayed rewards. *Journal of Experimental Psychology-General*, 126(1), 54-70.

Knack, S., & Keefer, P. (1997). Does social capital have an economic payoff? A cross-country investigation. *The Quarterly Journal of Economics*, 112(4), 1251-1288.

Kremer, M., & Miguel, E. (2007). The illusion of sustainability. *The Quarterly Journal of Economics*, 122(3), 1007-1065.

Krishna, A., & Shrader, E. (2000). Cross-cultural measures of social capital: a tool and results from India and Panama. *Social capital initiative working paper*, 21.

La Porta, R., Lopez-De-Silanes, F., Shleifer, A., & Vishny, R. W. (1996). Trust in large organizations. *National Bureau of Economic Research*.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics*, 112(2), 443-478.

Larrick, R. P., & Soll, J. B. (2008). The MPG illusion. *SCIENCE-NEW YORK THEN WASHINGTON*, 320(5883), 1593.

Lederman, D., Loayza, N., & Menendez, A. M. (2002). Violent crime: does social capital matter? *Economic Development and Cultural Change*, 50(3), 509-539.

Lee, K., Miguel, E., & Wolfram, C. (2016). Experimental Evidence on the Demand for and Costs of Rural electrification. *National Bureau of Economic Research*.

Liebman, J. B. (2004). Schmeduling Jeffrey B. Liebman and Richard J. Zeckhauser Harvard University and NBER.

Madrian, B. C., & Shea, D. F. (2001). The power of suggestion: Inertia in 401 (k) participation and savings behavior. *The Quarterly Journal of Economics*, 116(4), 1149-1187.

Manski, C. F. (2000). Economic analysis of social interactions. *National Bureau of Economic Research*.

Mansuri, G., & Rao, V. (2004). Community-based and-driven development: A critical review. *The World Bank Research Observer*, 19(1), 1-39.

McEachern, M., & Hanson, S. (2008). Socio-geographic perception in the diffusion of innovation: solar energy technology in Sri Lanka. *Energy Policy*, 36(7), 2578-2590.

Menon, G. (1993). The effects of accessibility of information in memory on judgments of behavioral frequencies. *Journal of Consumer Research*, 20(3), 431-440.

Menon, G., Raghbir, P., & Schwarz, N. (1995). Behavioral frequency judgments: An accessibility-diagnosticity framework. *Journal of Consumer Research*, 22(2), 212-228.

Mitchell, R. C., & Carson, R. T. (1989). *Using surveys to value public goods: the contingent valuation method*: Resources for the Future.

Morss, M. F. (1989). The incidence of welfare losses due to appliance efficiency standards. *The Energy Journal*, 10(1), 111-118.

Mullainathan, S., & Thaler, R. H. (2000). Behavioral economics. *National Bureau of Economic Research*.

Myerson, J., & Green, L. (1995). Discounting of delayed rewards: Models of individual choice. *Journal of the experimental analysis of behavior*, 64(3), 263-276.

Narayan, D., & Pritchett, L. (1999). Cents and sociability: Household income and social capital in rural Tanzania. *Economic Development and Cultural Change*, 47(4), 871-897.

Nieuwenhout, F., Van Dijk, A., Lasschuit, P., Van Roekel, G., Van Dijk, V., Hirsch, D., . . . Wade, H. (2001). Experience with solar home systems in developing countries: a review. *Progress in Photovoltaics: Research and Applications*, 9(6), 455-474.

Nieuwenhout, F., Van Dijk, A., Van Dijk, V., Hirsch, D., Lasschuit, P., Van Roekel, G., . . . Wade, H. (2000). Monitoring and evaluation of Solar Home Systems. Experiences with applications of solar PV for households in developing countries. *Netherlands Energy Research Foundation ECN*.

O'Donoghue, T., & Rabin, M. (1999). Doing it now or later. *American Economic Review*, 103-124.

Pashler, H., Johnston, J. C., & Ruthruff, E. (2001). Attention and performance. *Annual review of psychology*, 52(1), 629-651.

Rabin, M. (1998). Psychology and economics. *Journal of economic literature*, 36(1), 11-46.

RGPH. (2009). Recenseamento Geral da População e Habitacão

Roland, S., & Glania, G. (2011). Hybrid mini-grids for rural electrification: Lessons learnt. *Alliance for Rural Electrification (ARE)/USAID. Brussels, Belgium*.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of risk and uncertainty*, 1(1), 7-59.

SNV. (2011). Portrait of renewable energy in Guinea Bissau. Bissau July 2011

Tarozzi, A., Mahajan, A., Blackburn, B., Kopf, D., Krishnan, L., & Yoong, J. (2014). Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in Orissa, India. *The American economic review*, 104(7), 1909-1941.

Tarozzi, A., Mahajan, A., Yoong, J., & Blackburn, B. (2009). Commitment mechanisms and compliance with health-protecting behavior: Preliminary evidence from Orissa, India. *The American economic review*, 99(2), 231-235.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior & Organization*, 1(1), 39-60.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, 8(3), 201-207.

Thaler, R. H. (1999). Mental accounting matters. *Journal of Behavioral decision making*, 12(3), 183.

Thaler, R. H., & Shefrin, H. M. (1981). An economic theory of self-control. *Journal of Political economy*, 89(2), 392-406.

Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). *The psychology of survey response*: Cambridge University Press.

Train, K. (1985). Discount rates in consumers' energy-related decisions: A review of the literature. *Energy*, 10(12), 1243-1253.

Turrentine, T. S., & Kurani, K. S. (2007). Car buyers and fuel economy? *Energy Policy*, 35(2), 1213-1223.

Tversky, A., & Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases. In *Utility, probability, and human decision making* (pp. 141-162): Springer.

Tversky, A., & Kahneman, D. (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics, 106*(4), 1039-1061.

Tversky, A., & Shafir, E. (1992). Choice under conflict: The dynamics of deferred decision. *Psychological science, 3*(6), 358-361.

Urmee, T., Harries, D., & Schlapfer, A. (2009). Issues related to rural electrification using renewable energy in developing countries of Asia and Pacific. *Renewable Energy, 34*(2), 354-357.

Wang, S. (2009). Social capital and Rotating Labor Associations: An instrumental variable approach. *Working paper, Department of Economics, The University of British Columbia*.

WEO. (2011). Energy for All. Paris, France: OECD/IEA; 2011.

WEO. (2016). Energy for All. Paris, France: OECD/IEA; 2016.

Whittington, D. (2004). Ethical issues with contingent valuation surveys in developing countries: A note on informed consent and other concerns. *Environmental and Resource Economics, 28*(4), 507-515.

Woolcock, M. (1998). Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory and society, 27*(2), 151-208.

World Energy Outlook defining and modelling energy access.
<http://www.worldenergyoutlook.org/resources/energydevelopment/definingandmodellingenergyaccess/>. Retrieved 17/6/2015

World Energy Outlook energy access database.
<http://www.worldenergyoutlook.org/resources/energydevelopment/energyaccessdatabase/>. Retrieved 17/6/2015

Chapter 2

Willingness to pay for solar home systems in Guinea-Bissau: consumers' preferences for different delivery models

Abstract

Solar home systems are a viable alternative to achieve energy access in developing countries especially in areas lacking grid infrastructure. But despite their important potential there is a dearth of research in measuring the demand for these products and understanding its determinants. This stated preference study uses a choice experiment to estimate willingness to pay for a solar home system, and how it changes for different delivery models offering different repayment schemes and maintenance responsibilities within the region of Bafatá in Guinea-Bissau. Results suggest that rental schemes capture the largest market share in comparison to upfront payment and credit schemes. Preferences are driven by income limitations as well as discount rates. In addition, there is some evidence that individuals exhibiting hyperbolic discounting have a preference for credit schemes and lack of trust for actors within the community leads to a lower preference for delivery models that entail monthly repayments (i.e. rental, credit). Implicit discount rates inferred from preferences for repayment over time, confirm certain priors regarding discounting anomalies that have been outlined in the discounting literature, namely excessive discounting, preference heterogeneity and hyperbolic discounting.

1. Introduction

‘Energy poverty’ is a widespread problem in developing countries with serious economic and social implications (See Chapter 1). One of the potential technological solutions to address lack of electrification are solar home systems (SHS), which are isolated off-grid solutions that use photovoltaic modules to power households. The advantage of SHS rests in their ability to bypass grid infrastructure, which is often too costly to expand in areas currently lacking access.

A number of factors impeding wider SHS adoption have been identified. These are namely high upfront costs, limitations regarding the type and size of appliances that can be used and burdensome maintenance responsibilities (Nieuwenhout et al., 2001; Nieuwenhout et al., 2000; Urmee, Harries, & Schlapfer, 2009). Different delivery models have been designed to address the barriers of upfront costs and maintenance responsibilities. Specifically, credit schemes offer the option to consumers to repay for their SHS in instalments over time instead of having to pay high upfront costs; and rental schemes offer the additional option to consumers to free themselves from maintenance responsibilities.

For successful product design and dissemination, it is important to understand the impact that these delivery models and their respective characteristics have on demand as well as the underlying factors that drive the preferences of consumers.

This chapter uses a hypothetical choice experiment to estimate willingness to pay (WTP) for a SHS in rural Guinea-Bissau and how this WTP changes for different delivery models, which involve trade-offs between upfront costs and monthly payments, and different maintenance responsibilities. We also test if consumers’ preferences are driven apart from income limitations, by discounting irregularities, namely high discount rates and hyperbolic discounting and factors relevant to the social context, namely trust for different actors.

As discussed in Chapter 1 quite a few explanations have been suggested for the disproportionate negative impact of upfront costs on technology adoption. Amongst these are high discount rates, hyperbolic discounting and the influence of the social context in decision making.

Hyperbolic discounting, and high discount rates have been shown to negatively affect the adoption for a number of products with high upfront costs in a number of studies. These consist of energy consuming appliances in developed countries and health product and fertilizers in developing countries (Newell & Siikamäki, 2014; Bradford, Courtemanche, Heutel, McAlvanah, & Ruhm, 2014; Duflo, Kremer, & Robinson, 2011; Dupas & Robinson, 2013). In addition, it has been shown that individuals with hyperbolic preferences or social

pressures to share money are unable to save in order to meet investments in health technologies (Dupas & Robinson, 2013). On the other hand the social context is maintained to be able to affect technology adoption positively through facilitating risk sharing and contributing to the diffusion process (Narayan & Pritchett, 1999).

Credit and saving schemes have been suggested as a way to deal with these barriers as they have worked as commitment devices for individuals exhibiting hyperbolic discounting or social pressures to share money and increase their investments in health products (Dupas & Robinson, 2013). Similarly, credit schemes can also help individuals to deal with non behavioural barriers to adoption (e.g. income and liquidity constraints) (Tarozzi et al., 2014). However, the role of rental and credit schemes in the context of SHS to address income as well as barriers to adoption linked with high discount rates, hyperbolic discounting and the social context has not been explored.

Apart from drawing information from literature on discounting, this study also contributes to a strand of the discounting literature that infers implicit discounting rates by observing consumer choices for different energy consuming products that entail trade-offs between upfront and recurring costs (e.g. Revelt & Train, 1998; Hauseman, 1979; Allcott & Wozny 2014). By observing consumer trade-offs between different intertemporal payments this study tests the validity of these methods and the replicability of the findings (high discount rates and the systematic variation of discount rates between different time intervals, amongst different individuals and amongst different goods) in the context of demand for different delivery models of SHS. We are also able to test some correlates of these implicit discount rates (discount rates, hyperbolic discounting, trust for different actors) that is more difficult to do in the case of observational studies (Newell & Siikamäki, 2014).

We use a hypothetical choice experiment (CE), conducted in 149 households in rural Guinea-Bissau so we can measure the demand for a SHS product, the trade-offs between upfront payments and payments that recur monthly, and the value of maintenance responsibilities. Hypothetical stated preference methods were needed as there is not enough product variation in the market to use revealed preference methods (Benton, Meier, & Sprenger, 2007). A separate elicitation of time preference was included to test for the role of discount rates and hyperbolic preferences on delivery model choice. Finally, questions on trust regarding formal and informal institutions were included.

Results suggest that although preferences are heterogeneous, rental schemes capture the largest market share, in comparison to upfront and credit schemes. In addition, expressing a firm disinterest in purchasing the product, is driven by the limitations in the SHS features

(lack of television). Overall, preferences are driven both by income limitations as well as behavioural factors namely self-control problems, excessive discounting and trust for different actors. Specifically, demand for credit and upfront schemes is higher for higher income households and lower for individuals with high discount rates. In addition, individuals that exhibit hyperbolic preferences have a higher demand for credit schemes which is an indication that credit schemes are seen as a form of commitment mechanism to deal with self-control problems. Finally, those with lower self-reported trust for actors within the community have a lower demand for delivery models entailing monthly repayments. One explanation is that they have less people to rely on in case they are unable to meet their monthly repayments. At the same time, pressures within the household to share money was not found to affect preference for delivery models. Finally, implicit discount rates calculated confirmed certain priors regarding discounting anomalies that have been outlined in the literature on discounting, namely excessive discounting, preference heterogeneity and time preference reversals.

These findings have important policy implications as they demonstrate that there is high demand for SHS, in the context of rural Guinea-Bissau, which can be unlocked with the right delivery model design that could help meet both income as well as behavioural and social limitations. In addition, the existence of heterogeneity amongst consumer preferences suggests offering a range of different delivery options to consumers from which they can choose from.

This study is structured in the following way: In Section 2 we present the case study. Section 3 provides a literature review, while Section 4 presents the conceptual framework and the experimental design. Section 5, contains the results and Section 6 concludes.

2. Case study

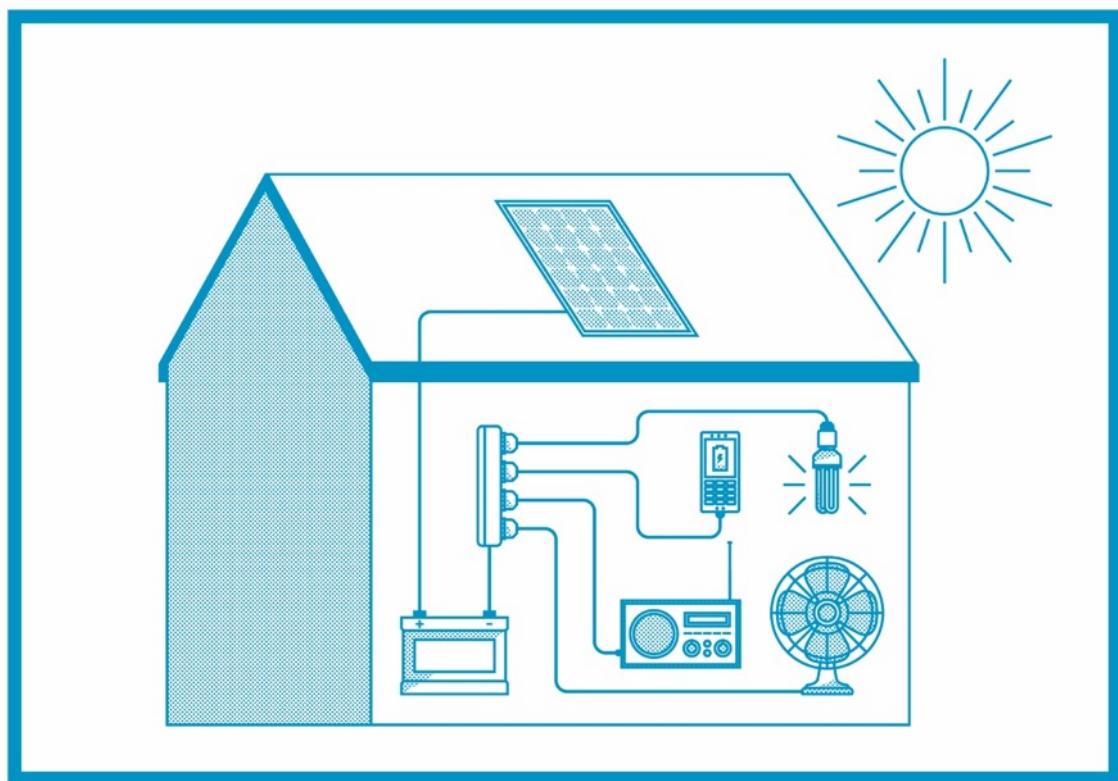
2.1 SHS and their delivery models

SHS are isolated off-grid solutions that use photovoltaic (PV) modules to electrify households. A PV panel is installed on a roof, converts solar energy to electricity and charges a storage battery, which is controlled by a charge regulator, and can be used to power equipment when there is no sunlight (See Figure 1).

A big variety in SHS in terms of sizes and services is offered in developing countries. These can range from small portable solar lanterns with limited lighting services to larger systems that permit the use of a number of appliances (e.g. TV, radio, mobile charger, fan,

fridge etc.). Services offered, depend on the wattage of the system, the battery capacity, efficiency of appliances used and sunlight availability. But in general, the needs met through SHS are usually limited, and therefore these systems are not direct substitutes of grid electricity. They are often seen in areas where grid extension is impossible or as a temporary solution in areas where the grid will be extended (Nieuwenhout et al., 2000). In addition, SHS have limited scope for income generating activities in comparison to other electricity solutions, but could provide opportunities for businesses through additional operating hours and refrigeration (Nieuwenhout et al., 2001).

FIGURE 1 EXAMPLE OF A SOLAR HOME SYSTEM



A PV PANEL IS INSTALLED ON A ROOF, CONVERTS SOLAR ENERGY TO ELECTRICITY AND CHARGES THE STORAGE BATTERY WHICH IS CONTROLLED BY A CHARGE REGULATOR.

Due to their reliance on a renewable resource, SHS require no operating costs, however they entail high upfront capital costs as well as expensive maintenance requirements. Specifically, batteries, which constitute a big part of the initial capital cost, deteriorate and need to be replaced every four or five years. These high upfront costs and expensive maintenance,

constitute the main adoption barriers in developing countries (Nieuwenhout et al., 2001; Nieuwenhout et al., 2000; Urmee et al., 2009). Consumer credit and rental schemes are delivery models that have been designed to address these barriers and render SHS more widely affordable (Nieuwenhout et al., 2001; Nieuwenhout et al., 2000).

Consumer credit and rental schemes are delivery models designed to overcome the problems of high upfront costs required by upfront schemes, in which consumers are required to pay the full price of the system in one instalment. When credit is provided, the customer needs to pay only a small upfront cost and repay the rest of the loan in monthly instalments with a certain interest. In the rental scheme the customer is only required to pay monthly fees for the time he/she uses the system. However, there is usually a price premium for not paying the full cost of the system upfront, which is usually higher in rental schemes than in credit.

From the customer's perspective, an additional benefit of a rental scheme is that the maintenance responsibilities rest with the programme implementers. However, customers lack ownership of the system. Ownership is usually desirable unless there are expectations for imminent connection to the grid (Nieuwenhout et al., 2001). From the seller's point of view when the systems are rented out, there is a danger that the customer will not maintain the system properly, as lack of ownership gives no incentive to the consumer to maintain the system's performance. In addition, both rental and credit schemes entail higher transaction costs and increased incidence of repayment delays and defaults. Table 1 provides information on the characteristics of the different delivery models based on full cost recovery (adopted from Nieuwenhout et al., 2000).

TABLE 1 CHARACTERISTICS OF DIFFERENT DELIVERY MODELS

Delivery model	Ownership	Financing	Maintenance
Upfront (Cash sales)	Customer		Customer
Credit	Customer	Commercial bank, cooperative, dealer, International donor	Customer/ Service company
Rental (Fee for service)	Energy Service Company (ESCO)	ESCO	ESCO

Adopted from Nieuwenhout et al., 2000

2.2 'Lojas Sta Claro' project

'Lojas Sta Claro' is a project proposed by TESE- Development Association (TESE), a Portuguese non-governmental organization (NGO) working on infrastructural projects in Guinea-Bissau. This project, which has not reached the implementation stage yet, aims to service the region of Bafatá in Guinea-Bissau with a range of SHS products and delivery models that the consumer can choose from. The project is called 'Lojas Sta Claro', which in the local Portuguese Creole language means 'the store it is illuminated'.⁷

Three different products have been proposed to address the needs of low income, medium and upper income groups⁸, as well as businesses (see Appendix for more details). This study focuses on the product proposed for the medium to upper income group. This is a 20 peak watts (Wp) system that can power 4 fluorescent lights and has an outlet to plug in a mobile charger, a radio and a fan. The lights can be used for 7 hours a day and the radio, fan and charger for a few hours a day, depending on the use of the rest of the equipment. Figure 2 provides a schematic representation of the product.

The lifetime of the system is estimated to be 10 years. As far as replacements are concerned the battery will need replacement on average every four years and the lights and fuses once in the lifetime of the system (every 8 years). No more replacements are anticipated unless parts break unexpectedly.

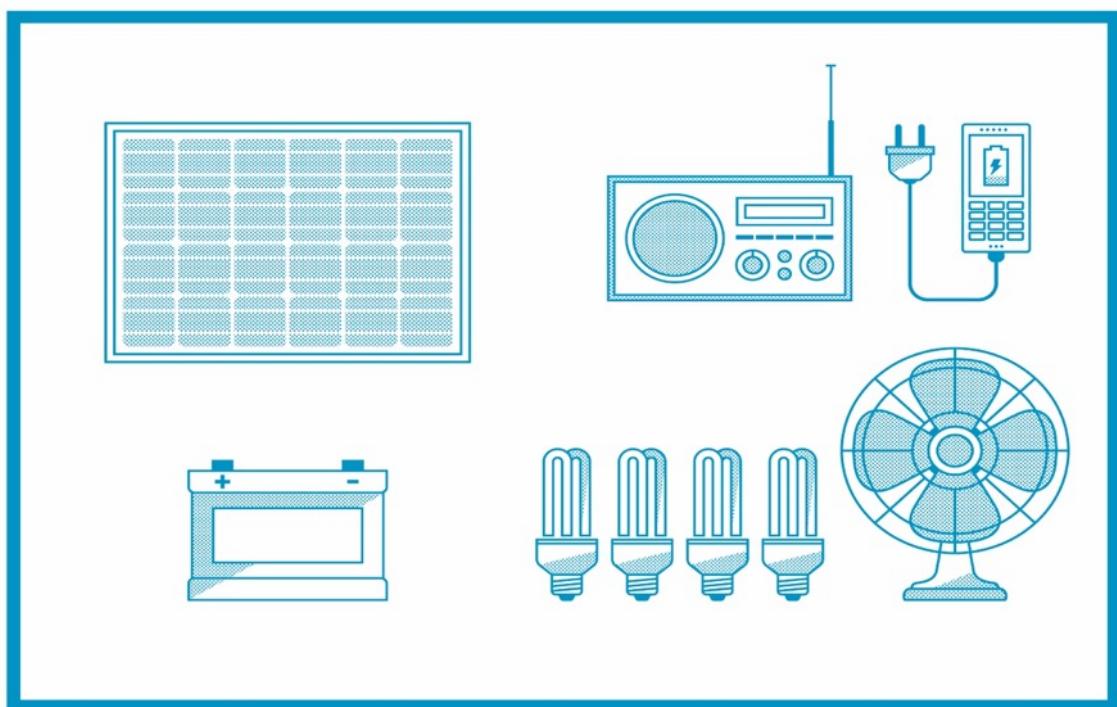
The prices proposed for each delivery model and the expected maintenance costs are shown in West African CFA Francs in Tables 2 and 3⁹.

⁷ The name comes from the 'Bambadinca Sta Claro' project described in detail in the following chapters and it relates to a different approach suggested by TESE when centralized solutions are not viable.

⁸ TESE classified these income groups in the following way: the Lower income group has a monthly income of around 25 USD, the Medium/upper income group has a monthly income of around 34 USD.

⁹ The local currency is the West African CFA Franc, also represented as XOF or FCFA. The current conversion rate is 633 FCFA to 1 USD. However, prices were calculated based on the 2013 conversion rate (500 FCFA to the dollar) when this study was designed. Prices were originally proposed in dollars and converted to the local currency when this study was designed in the autumn of 2013. Therefore, in the case of project implementation it remains unclear how these prices would change, also given the potential technological advances since.

FIGURE 2 SCHEMATIC REPRESENTATION OF PRODUCT UNDER VALUATION



SOLAR PANEL WITH A CAPACITY OF 20 PEAK WATTS (Wp) AND A STORAGE BATTERY. THE SYSTEM CAN POWER 4 FLUORESCENT LIGHTS AND HAS AN OUTLET TO PLUG A MOBILE CHARGER, A RADIO AND A FAN.

TABLE 2 PROPOSED PRICES FOR EACH DELIVERY MODEL

	Upfront	Credit ¹⁰	Rental
Price (FCFA)	100,000	4,000 per month (for two years)	4,000 per month
Maintenance	Customer	Customer (once the system is repaid)	Service company

Information adopted from TESE 'Lojas Sta Claro' project proposal

TABLE 3 EXPECTED MAINTENANCE AND REPLACEMENT COSTS

	Battery	Lamps	Fuses
Replacement price (FCFA)	43,300	1,000-2,000	600
Replacement rates	Every 4 years	Every 8 years	Every 8 years

Information adopted from TESE 'Lojas Sta Claro' project proposal

¹⁰ The credit option was not available in the last project proposal by the NGO, but it is still discussed as a potential option. Therefore, we kept it as an option in our study.

2.3 Location description Guinea-Bissau & Bafatá

This study took place in the Bafatá region of Guinea-Bissau (See Chapter 1 for a description).

3. Literature review

This work is drawing from, and contributing to, three different strands of literature, namely the literature on discounting and technology adoption, the literature on applications of stated preference methods in renewable energy, and the literature on adoption of SHS in developing countries.

3.1 Discounting and technology adoption

There is a broad number of studies eliciting discount rates. Overall, a number of anomalies have been observed as in contrast to expectations from rational economic theory these discount rates tend to be higher than expected and to vary between individuals, between different time frames and between different goods and to be sensitive to the decision environment (see Frederick et al., 2002 for a review).

These findings have been used to inform policy including energy policy and technology adoption in developing countries (see Chapter 1). This study contributes to this literature by looking at how some of these anomalies (excessive discounting, hyperbolic discounting, the influence of the social context) apply in the case of SHS adoption in developing countries and can be addressed by different delivery models. In addition, this study contributes to the discounting elicitation literature.

One way to elicit discount rates is through lab experiments or artefactual field experiments where individuals are asked directly to express their time preferences for real or hypothetical goods through choice tasks, matching tasks, pricing tasks or rating tasks (e.g. Harrison, Lau, & Williams, 2002; Thaler, 1981).

The other way to elicit discount rates is to observe the actual behaviour of individuals in instances where decisions that reveal time preferences are made. These usually look at trade-offs between upfront payments and recurring costs or choices between one-off receipts and recurring receipts. Such studies include, among others, observed purchases for energy

consuming appliances, and vehicles which involve a trade-off between capital and operating costs.

Overall, the discount rates found in such studies range widely according to the methods used and the technologies studied. Most studies tend to find discount rates that are much higher than market interest rates which is in agreement with the 'efficiency gap' hypothesis. For example, the Hausman, 1979 study, which is the seminal study in the field, looks at purchases choices for air conditioners in the United States and finds the average implicit discount rate to be 26.4%, with income being an important determinant. Gately, 1980 finds similarly high discount rates for refrigerators which range from 45% to 300% depending on the brands and price assumptions. In a survey article Train, 1985 finds the range of implicit discount rates to be from 2% to above 100% depending on the methods and assumptions used as well as on the technology in question.

More recently Metcalf & Hassett, 1999 find a 9.7% implicit discount rate for attic insulation and Dreyfus & Viscusi, 1995 a range of 11-17% for automobiles.

Almost no such studies have been conducted in developing countries with the exception of Matsumoto & Omata, 2017 that look at the market for air conditioners in Vietnam and find the implicit discount rates to range from 11.7% - 312% (depending on size). Demonstrating that discount rates are higher in developing countries.

A number of hypothetical studies have also been conducted. Jaccard & Dennis, 2006 find a 20.79% implicit discount rate for home retrofits and 9% for space heating. Revelt & Train, 1998 find an implicit discount rate of 39% for refrigerators. Using a hypothetical choice experiment Min, Azevedo, Michalek, & de Bruin, 2014 find a 100% discount rate for light bulbs.

In all studies, assumptions have to be made concerning the lifetime of the product, the usage intensity and the development of future energy prices. In addition, it is not possible to factor in hidden costs or irrelevant product attributes that affect the purchase decision and often correlate with prices. Finally, even if average costs and benefits are calculated heterogeneity of consumers in terms of costs and benefits is not always taken into consideration. All these issues, can cause measurement errors (see Allcott & Greenstone, 2012 for a discussion).

The use of panel data allows researchers to control for time-invariant product attributes that cannot be observed. Using panel data for automobiles Allcott & Wozny, 2014 find a 15% discount rate and Busse, Knittel, & Zettelmeyer, 2013 as well as Sallee, West, & Fan, 2009 find that there is no efficiency gap. This demonstrates that the high levels of implicitly discount rates found in previous studies could be largely driven by factors irrelevant to time preference.

However, these studies still rely on assumption about prices levels and utilization intensity (see Allcott & Greenstone, 2012 for a discussion).

It is empirically difficult to isolate discounting behaviour from the choice environment or other considerations that affect the observed choices and are irrelevant to time preference. Research has shown that a number of factors could be affecting these purchase decisions (e.g. hyperbolic discounting, bounded rationality issues, social context, liquidity constraints, asymmetric information etc.) (See Chapter 1). However, more research is needed in order to understand the effects of each potential factor from competing explanations (see Geraden, Newell & Stavins, 2015). This is crucial not only for the time preference literature but to also understand what drives technology adoption decisions.

Hypothetical choice experiments provide us with the opportunity to explore these effects as they allow us to control the choice environment and to collect additional information on the respondents (Geraden, Newell & Stavins, 2015).

Newell & Siikamäki, 2014; 2015 through a hypothetical choice experiment explore the role of information provision on the demand of efficient appliances. They also conduct a separate elicitation of time preferences to control for the role of discount rates on these choices. They find that simple information provision on total costs has the biggest effect on the demand for more efficient appliances. They also find that there is a relationship between discount rates, and preference for less efficient energy using products with lower upfront costs (Newell & Siikamäki, 2015; Newell & Siikamäki, 2014).

The present study explores these dynamics further by looking not only at the role of discount rates on the purchase choices for an energy product, but also at the role of hyperbolic discounting and trust for different actors. We are not looking at choices regarding energy efficiency purchases, but choices for repayment over time for a SHS, which however also entail a time trade-off component. This also gives as the opportunity to explore if findings from other studies regarding discounting anomalies translate in the case of the context of SHS demand in developing countries.

3.2 Stated preference methods and demand for renewable energy

A sizeable number of stated preference studies has been conducted to measure renewable energy demand and its socio-economic determinants, but these mostly focus on developed countries, and predominantly on on-grid rather than off-grid solutions (Batley, Colbourne, Fleming, & Urwin, 2001; Bergmann, Hanley, & Wright, 2006; Nomura & Akai, 2004; Wiser, 2007).

Two studies apply a hypothetical CE on the study of energy in developing countries. Takama et al., 2012 use a hypothetical choice experiment to estimate consumer WTP for cookstove attributes in Ethiopia, and Abdullah & Mariel, 2010 use a hypothetical choice experiment to look at consumer preferences regarding grid supply reliability improvement in Kenya. Abdullah & Jeanty, 2011 use contingent valuation to estimate WTP for grid connections and standalone SHS in Kenya. Their study also includes a WTP estimate for one-off and recurring payments, however there is no focus on the different delivery models of SHS and their respective characteristics (Abdullah & Jeanty, 2011).

A number of studies use responses to state preference methods regarding repayment preferences over time to calculate implicit discount rates. Kim & Haab, 2009 conduct a contingent valuation to find WTP derived from a value elicitation survey on oyster reef restoration programs in the Chesapeake Bay for different payment schedules (one time, annual and perpetuity) and find the discount rates to range from 20% to 98% and to decline with the time horizon, as is consistent with hyperbolic discounting.

Kovacs & Larson, 2008 conduct a contingent valuation study to measure WTP for public space and the implicit discount rates for four different time frames of monthly repayments (for one year, four years, seven years and ten years) they find discount rates to range between 50%, 19% and 28% and to be higher for shorter time frames (average 30%).

Finally, Abdullah & Jeanty, 2011 find discount rates for grid and solar energy in Kenya to drop from 165% (grid) and 125% (solar) when compared to one year repayments to 45% (grid) and 35% (solar) when compared to five year repayments.

A larger application of stated preference studies in the study of energy in developing countries could help inform policy making for a broad range of issues (payment structure, project design, choice of technology etc.) in a field which is central to economic development and environmental policy. Our study is also offering insights of a case study conducted in a country with low human development and with severely limited access to energy.

3.3 SHS adoption literature

A number of studies on SHS adoption in developing countries that use quantitative discrete choice models have focused on identifying income and non-income determinants on the decision to adopt SHS (Adkins, Eapen, Kaluwile, Nair, & Modi, 2010; Komatsu, Kaneko, Shrestha, & Ghosh, 2011; McEachern & Hanson, 2008; Rebane & Barham, 2011; Voravate, Barnes, & Bogach, 2000). Household income, ownership of rechargeable batteries, kerosene consumption, number of mobile phones are just a few of the factors linked to the adoption decision in rural Bangladesh, and the number of children and concern about indoor air pollution are linked to the choice of panel size (Komatsu et al., 2011). Rebane & Barham, 2011 find adoption of SHS in rural Nicaragua to be predicted by income, geographical location and the way knowledge is acquired. They find that knowledge is better predicted by other installed SHS and certain individual characteristics. A number of other studies also look into the role of knowledge on SHS adoption and how it is achieved. Their findings demonstrate that word of mouth and other installed systems predominantly generate knowledge (Acker & Kammen, 1996; Voravate et al., 2000). McEachern & Hanson, 2008 explore the role of social capital on the decision to adopt SHS in Sri Lanka both at the individual and village levels. Their findings underscore the importance of breaking down social capital indicators as they conclude that different measures of social capital have opposing impacts to adoption decisions.

This study focuses on how different repayment schemes and maintenance responsibilities affect WTP for SHS. Although the importance of these factors for SHS adoption has been underscored in a number of case studies and best practice documents (see Nieuwenhout et al., 2001; Nieuwenhout et al., 2000 for a comprehensive review), there hasn't been an attempt to quantify preference for delivery method choice and its determinants.

4. Methodology

4.1 Choice experiments

Survey based choice experiments belong to the family of stated preference techniques. The CE method aims to calculate WTP for a product and its respective attributes by observing the trade-offs consumers make between the different levels of these attributes. CE have their theoretical foundations in the concept that goods are described by their respective attributes (Lancaster, 1966), and the Random Utility Model.

The Random Utility Model holds that individual n selects the alternative i with the highest utility U_{in} amongst his choice set C_n . This utility U_{in} is expressed in a systematic utility component V_{in} and a random utility component ε_{in} . The systematic component can be described as a linear function of observable variables describing the attributes of the alternative and characteristics of the individual.

$$U_{in} = V_{in} + \varepsilon_{in} = \beta' X_{in} + \varepsilon_{in}$$

Due to the existence of the error term, which contains everything else that is relevant to the choice of the respondent and is not observable, the selection process can be described with the following probability formula:

$$\begin{aligned} P(i|C_n) &= P[U_{in} \geq U_{jn}, \text{all } j \in C_n] \\ &= P[V_{in} + \varepsilon_{in} \geq V_{jn} + \varepsilon_{jn}, \text{all } j \in C_n] \\ &= P[V_{in} - V_{jn} \geq \varepsilon_{jn} - \varepsilon_{in}, \text{all } j \in C_n] \end{aligned}$$

This formula states that an individual n will choose option i over all other alternatives in the choice set if the difference in the utility of their systematic parts (observable part), is larger or equal than the differences between their error terms (unobservable part). Including the status quo as an option in the choice sets, it renders CE in accordance with demand theory and utility maximization, and allows for the measurement of WTP for changes in attribute levels and other welfare changes (Bateman & Langford, 1997).

Using this method, a series of choice sets were presented to respondents with varying levels of different attributes of the good in question.

4.2 Attributes and levels

The attributes of price and maintenance responsibilities were chosen for this study. An alternative specific design was chosen with three alternative specific constants representing each delivery model. The three delivery models were an upfront scheme where the user must pay everything upfront to acquire the system; a credit scheme where the user must pay monthly instalments for two years to acquire the system and a rental scheme where the user must pay a monthly fee for the entire time he uses the system which is a maximum of ten years (the estimated lifetime of the system). This number was used as an approximation to calculate discount rates as well as to calculate the total cost information that was presented to consumers to limit computational limitations and reduce the salience of upfront cost.

A labelled experiment (an alternative specific design) was chosen to select the price ranges independently for every delivery model. The three delivery models were presented next to each other with a fourth option of not buying the product (status quo). This choice framing was chosen to be closer to a real choice environment.

The attributes were chosen, based on the findings of the literature on SHS delivery models. Maintenance responsibilities were varied for all the three delivery models between two options: 1) all maintenance rests with the user and 2) all maintenance rests with the company for the lifetime of the system, with the sole responsibility of the owner to clean the panel once a month during the dry season. Regarding the choice of price levels, the prices proposed by the NGO and the estimated costs of maintenance, were taken into consideration. We followed a method previously used by a number of contingent valuation studies which measured implicit discount rates (Kim & Haab, 2009; Kovacs & Larson, 2008). Price levels were linked to each other with a discount rate (20% annual discount rate). In other words, the price levels from the upfront payment alternative, were divided by the number of repayment months (24 for credit and 120 for rental) and compounded with an annual interest rate of 20%. Following that procedure, prices were realistically rounded up and the upper range of the prices of the rental scheme were increased to capture the range of demand more appropriately. Seven different price levels were ultimately chosen. A summary of the attributes selected is set out in Table 4.

Realistically, in the credit and upfront delivery models, the maintenance responsibilities rest with the user, and in rental schemes the user has no maintenance responsibilities. Credit options could come with a form of insurance which is bundled in the price which exempts the user from at least some of the maintenance of the system (Nieuwenhout et al., 2000). The same could also apply for upfront schemes at least in theory. Therefore, the option to allow

maintenance to vary with the credit and upfront scheme was not considered problematic. However, as there is no case of a rental scheme with maintenance resting with the user, there were concerns that allowing maintenance to vary with the rental scheme would be deemed unrealistic by respondents, possibly leading to protest responses. However, there was no such indication during the pilot survey, and therefore maintenance was varied with all three delivery models so that we could disentangle its effects from repayment method preferences.

Finally, some potentially important attributes were not included in order to not make the choice exercise too complicated. Usually credit schemes also come with a smaller upfront payment to make sure that the user commits to repay the product (Nieuwenhout et al., 2000). In addition, other issues like weekly instead of monthly repayments (to resemble closer current energy spending practices), and flexible repayments in times of less income availability, were raised during the pilots and focus groups. These could potentially be important in shaping consumer preferences.

TABLE 4 ATTRIBUTES AND LEVELS CHOSEN FOR THE CHOICE EXPERIMENTAL DESIGN

	Upfront	Credit	Rental
Price (FCFA)	50,000	2,400	900
	70,000	3,400	1,200
	100,000	4,800	1,800
	140,000	6,700	2,500
	200,000	9,600	3,600
	280,000	13,400	5,000
	340,000	16,200	8,000
Maintenance responsibilities	User/Company	User/Company	User/Company

4.3 Choice set design

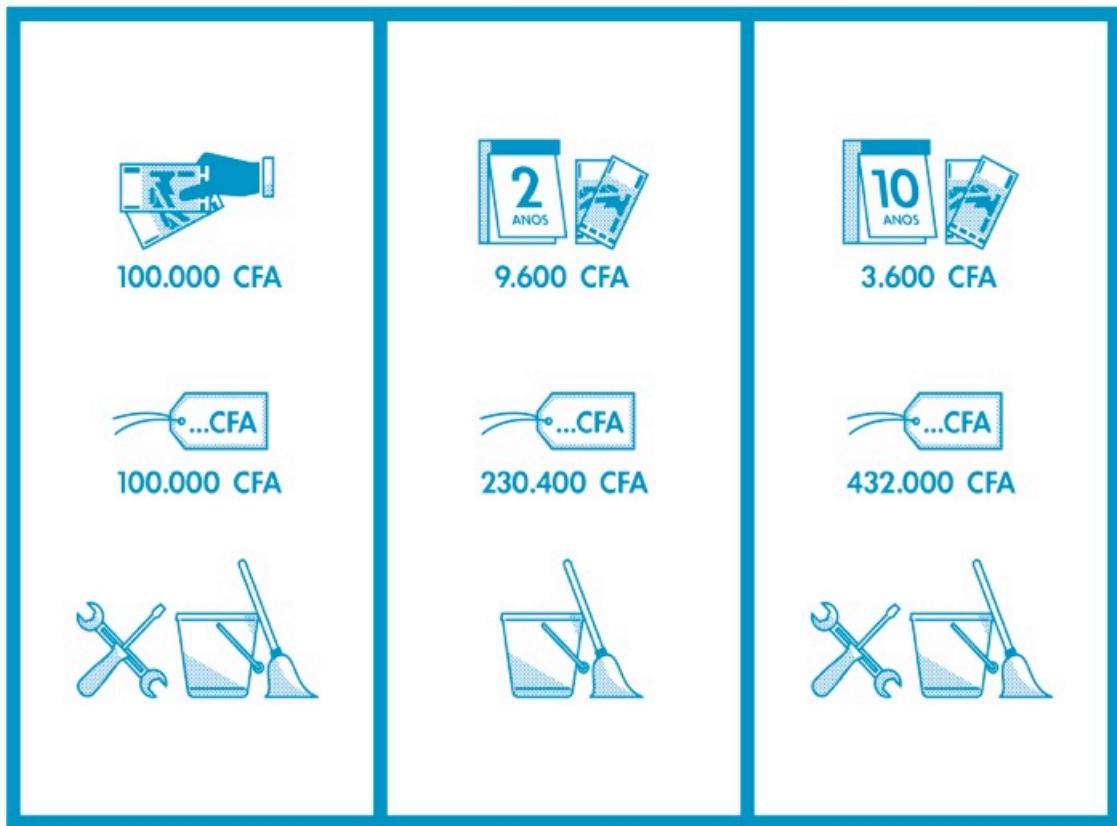
A full factorial design of attributes produces 2,744 ($7^3 \times 2^3$) possible scenarios. An orthogonal simultaneous main effects factorial design was generated using SPSS, which limited the scenarios to 49.

During the pilot, some of the respondents specifically expressed preference to upfront payments, even if it ended up being costlier to them than the other two options. This meant that the scenarios where upfront payments were of costlier overall, than the other two delivery models, were not deemed implausible. On the other hand, there were a few scenarios where the rental scheme entailed a higher level of monthly repayment than the credit scheme with the same maintenance responsibilities. These were deemed implausible. However, they were not removed as there was still a valid option between the other two schemes in the payment card. In addition, this was a way to check for consistency in responses, as has been done in other studies (Saelensminde, 2002). These 49 alternatives were impossible to handle by a single individual. Therefore, 4 out of the 49 alternatives were chosen without replacement of each individual.

Other types of experimental designs exist that are more efficient than orthogonal designs. However, these efficient designs are deemed appropriate for studies where priors are already available, or with large sample sizes (Ferrini & Scarpa, 2007; Lusk & Norwood, 2005). This was not the case in our study.

Images were introduced to reduce the cognitive burden required to interpret the choice sets (Figure 3). The hand giving the money represents upfront payments and the two different diaries explain the credit and the rental scheme. The price tag informs the respondent about the total costs of each option summing up monthly repayments. The image with the mop and bucket means that the user is only responsible for cleaning the system. The image with the mop, the bucket and the tools means that apart from cleaning the system the respondent is also responsible for all the replacements. Respondents were informed how much these maintenance responsibilities are expected to cost them. The status quo alternative (of not buying anything) is not represented with an image but was repeated every time by the interviewer.

FIGURE 3 EXAMPLE OF CHOICE CARD



THE HAND GIVING THE MONEY REPRESENTS UPFRONT PAYMENTS AND THE TWO DIFFERENT DIARIES EXPLAIN THE CREDIT AND THE RENTAL SCHEME. THE PRICE TAG INFORMS THE RESPONDENT ABOUT THE TOTAL COSTS OF EACH OPTION SUMMING UP MONTHLY REPAYMENTS. THE IMAGE WITH THE MOP AND BUCKET MEANS THAT THE USER IS ONLY RESPONSIBLE FOR CLEANING THE SYSTEM. THE IMAGE WITH THE MOP, THE BUCKET AND THE TOOLS MEANS THAT APART FROM CLEANING THE SYSTEM THE RESPONDENT IS ALSO RESPONSIBLE FOR ALL THE REPLACEMENTS. THE STATUS QUO ALTERNATIVE (OF NOT BUYING ANYTHING) IS NOT REPRESENTED WITH AN IMAGE BUT WAS REPEATED EVERY TIME BY THE INTERVIEWER.

4.4 Limitations

A number of biases are prevalent in stated preference methods affecting the validity and reliability of the estimates. Mitchell & Carson, 1989 discuss a number of limitations in contingent valuation which apply to hypothetical stated preferences methods in general including CE. One of the main limitations they refer to is linked to the hypothetical nature of stated preference methods which can lead to non-meaningful, often unrealistically high, responses.

This finding, termed by many researchers as 'hypothetical bias', has been shown to exist in a number of experimental studies or meta-analysis comparing real and hypothetical

payments both for contingent valuation (Mjelde, Jin, Lee, Kim, & Han, 2012; Murphy, Allen, Stevens, & Weatherhead, 2005) and CE (Lusk & Schroeder, 2004).

Another source of bias discussed by Mitchell & Carson, 1989 is linked with the inability of respondents to take into consideration external information when making their choices in a hypothetical scenario (budget constraints, substitutes). Similarly, strategic behaviour is also a danger in stated preference methods, where responses are not truthful, but instead driven by considerations to affect policy regarding the provisions of a good and the levels of payment. Protest responses where respondents out of protest to an aspect of the hypothetical market refuse to participate or give extreme responses can also bias the results. Finally, a number of survey related biases are relevant and can affect the accuracy of responses like interviewer bias and the way the information is communicated to respondents (Mitchell & Carson, 1989).

Other issues that might determine the accuracy of stated preference methods is that the choice of the property right can make a substantial difference in the results due to the observed discrepancy between between willingness to pay (WTP) and willingness to accept (WTA), with WTA being higher also for reasons emanating from behavioural economics like status quo bias and endowment effect (see Horowitz & McConnell, 2002 for a review). Finally, in the valuation of public goods (with significant non-use values) respondents have been shown to state similar values for different levels of goods in contingent valuation surveys (e.g. Desvouges et al., 1992 birds and oil spills). One explanation behind this phenomenon is that the responses are mostly driven by the gratification individuals get from giving money for public goods rather than from the actual economic value of these goods (Kahneman & Knetch, 1992). However, this is not an issue in the case of the valuation of private goods and is also less relevant in the case of choice experiments (Adamowicz, 1995).

There are also some biases specific to choice experiments which are more cognitively demanding than other stated preference methods. Specifically, responses can be sensitive to the study design (choice of attributes, price levels) (Hanley, Mourato, & Wright, 2001). In addition, choosing between a different number of goods that each contain different level of attributes can result to fatigue and inconsistent behaviour (Hess, Rose, & Polak, 2010) and as DeShazo & Fermo, 2002 show this inconsistent behaviour occurs when the complexity of the choice experiment increases. Finally, non-trading and/or lexicographic preferences where responses are driven only by one or a sub-set of attributes, or by rules of thumb have been also observed (Hess, Rose, & Polak, 2010; Campbell, Hutchinson, & Scarpa, 2006). However, these lexicographic preferences and non-trading could also be reflecting actual decision making patterns (Hess, Rose, & Polak, 2010).

Despite these limitations Carson, Flores, Martin, & Wright, 1996 in a review find that stated preferences and revealed preference studies give similar results. As Mitchell & Carson, 1989 stress with the right design (e.g. neutral information, realistic scenarios, good description of good and payment vehicle, pretesting) results can be meaningful.

In addition, a series of meta-analysis studies and experiments find that hypothetical bias is reduced with increased familiarity of respondents with the good under valuation (Mjelde, Jin, Lee, Kim, & Han, 2012) and when respondents are encouraged to respond truthfully (Carlsson, Frykblom, & Lagerkvist, 2005; Cummings & Taylor, 1999). There is also evidence that the valuation of private goods leads to lower hypothetical bias possibly due to increased familiarity (Murphy et al., 2005; List & Gallet, 2001; Atkinson & Mourato, 2008). Finally, in the case of CE smaller number of choices and less complicated tasks reduce the risk of fatigue and inconsistent preferences (Hess, Rose, & Polak, 2010).

A combination of measures was used to reduce the potential sources of bias that were relevant for this study namely hypothetical bias, strategic bias, focusing bias and non-trading. In our study respondents have high familiarity with the product under valuation as it is already available in the marketplace. In addition, the legitimacy of the payment vehicle was reinforced through the affiliation with an NGO operating in the area, which is expected to limit strategic responses (Mitchell & Carson, 1989). Before the CE commenced, respondents were encouraged to give honest responses. In addition, to limit focusing bias and non-trading, after every choice follow up questions were included. This was done to make sure that respondents were taking into consideration all the attributes of the choice card as well as their budget limitations, and that each choice was independent from previous choices. It was also emphasized that responses will not have any effect on how the product will be offered to the communities.

Steps were also taken to limit cognitive limitations and ensure that respondents understood the product they were asked to value. Before the CE commenced some familiarity questions about SHS were introduced to induce the respondent to start thinking about the product. After that, the product and its features were presented to the respondents in detail, using images (see Figure 1 and Figure 2). Finally, to explain the CE exercise, respondents were shown images of the different product attributes and their levels.

Finally, in the ‘Results’ section we will show that results confirm a number of priors regarding consistency with economic theory, as far as the effect of the price and income levels are concerned (construct validity) (Carson, Flores & Meade, 2001).

4.5 Other survey questions

4.5.1 Trust questions

As is common practice in surveys measuring aspects of social capital (e.g. General Social Survey, World Bank Social Capital Initiative¹¹), respondents were asked to report their level of agreement with statements expressing their level of trust regarding different actors in a five-point scale¹² (traditional leaders, local government, NGOs and individuals within their community).

4.5.2 Time preference questions

A choice task protocol to elicit discount rates was used, drawing from common practices in literature (see Frederick et al., 2002). Respondents were asked to report their preference between receiving a smaller amount of money now and a larger amount in a month from now. ‘If someone offered you a guaranteed 1,000 FCFA today, or a guaranteed 1,500 FCFA in a month’s time, which would you prefer?’. The same question was posed 10 times, each time increasing the amount offered in the future date,¹³ until the point where the respondent chose the future option. The current amount offered was set to 1,000 FCFA. This amount was chosen to be substantial as compared to average consumption habits. There have been similar considerations by other authors (Ashraf et al., 2006; Dupas & Robinson, 2013). We had no information about the average household daily expenditure for the region of Bafatá prior to the study. However, a baseline survey conducted in the community of Bambadinca, situated in the Bafatá region, in 2010 by TESE found the average daily expenditure by household to be 2,052.75 FCFA (TESE, 2010).

The midpoint of the range at which the individual chooses the amount offered in the future is assumed to be his discount rate. The same sets of choices were offered in a year from now to test for preference reversals. ‘If someone offered you a guaranteed 1,000 FCFA in 12 months, or a guaranteed 1,500 FCFA in 13 months, which would you prefer?’. The time frame

¹¹ The Social Capital Initiative refers to an effort by the World Bank to provide a better definition and measurement for the concept of social capital in the context of development. See (Krishna & Shrader, 2000) for an example of questionnaire design.

¹² Five-point scale: trust a lot, trust, not trust nor distrust, distrust, distrust a lot.

¹³ The amounts in FCFA were: 1,500, 2,000, 2,500, 3,000, 3,500, 4,000, 4,500, 5,000, 8,000, 12,000.

was moved to a year from now to control for seasonality effects which are prevalent in rural Guinea-Bissau. Individuals who exhibited lower discount rates in the second part of the time preference questions are assumed to be hyperbolic discounters. Although this could be a moderate estimate of hyperbolic discounting (as it was not asked at different points in the survey to avoid responses being driven by a desire to give consistent answers) (Ashraf et al., 2006), it has been shown to remain a robust prediction of hyperbolic preferences and self-control problems (Bauer et al., 2012).

Not all time discounting issues are addressed in this elicitation method (absence of risk elicitation, assumption of linearity of utility function, hypothetical choices, absence of front-end delay) (Frederick et al., 2002; Harrison, Lau, & Williams, 2002). The absence of risk elicitation and real rewards was due to the fact that it was logistically difficult for us to return to the field a year latter to make the payments according to the responses on the question measuring time preference reversals. It was also linked to our decision to not include monetary rewards for survey participants (discussed in Chapter 1). There is a general preference in the literature for real payments when eliciting discounting preferences as they are expected to give more accurate answers. For example, in an experiment comparing time preference elicitation made with real and with hypothetical payments Coller & Williams, 1999 find that results are significantly different and that responses with real rewards have a lower unexplained variance. However, a number of other similar experiments have shown no significant differences between discount rates elicited with real and hypothetical rewards within subjects (Johnson & Bickel, 2002; Madden, Begotka, Raiff, & Kastern, 2003)

In addition, Vischer et al., 2013 find that survey questions measuring impatience predict well discount rates elicited with real payments. Finally, the absence of front-end delay is mostly linked to bias when real payments are involved (Harrison et al., 2002), which is not the case in our study.

Importantly, time preference elicitation with hypothetical rewards are used in many studies (e.g. Thaler, 1981) especially in contexts where flexibility is required (Frederick et al., 2002). Similar choice tasks to ours have been used in other studies and shown to be robust in predicting behaviour in developing countries (Ashraf et al., 2006; Dupas & Robinson, 2013).

4.6 Implementation

The design of the survey was led by interviews with local stakeholders and households using similar products, two pilot surveys, in some of the surveyed communities and background work done by the partnering NGO during the stage of product design.

The first survey pilot took place between the 9th and the 11th of December 2013 in three different villages (tabancas) in the Bafatá region (Bidjini, Bricama, Djabicunda). Overall 8 individuals were interviewed. The aim was to test the choice cards for their clarity, to try different combinations of product attributes and explore the best wording to avoid potential bias. The aim was also to increase comprehension of the choice exercise. The survey was also tested to see how to structure the different parts of the questionnaire. Community dynamics and potential problems that could arise during the survey were also detected.

Finally, the first two weeks of the actual survey were also designated as a pilot, but as no changes were made, surveys were incorporated in the result analysis.

The final CE survey was undertaken in nine communities of the Bafatá region in Guinea-Bissau, presented in Table 5. A non-probabilistic convenience sample was chosen, based on considerations to include communities which differ in terms of isolation, energy poverty and urbanization. These communities included 4 out of the 6 ‘phase 1’ communities indicated from the NGO as the communities with the greater potential for immediate dissemination. The rest were peripheral communities considered by the project implementers as part of the ‘phase 2’ communities. In addition, households with large visible SHS were not surveyed. This is not a representative sample of the Bafatá region. It is however, a convenience sample of potential clients of the first stages of the project. A map of the surveyed communities can be found in the Appendix.

TABLE 5 SURVEYED COMMUNITIES

	Frequency	Percent	Phase 1 Communities
Bidjine	28	18.79	Yes
Bricama	9	6.04	No
Buntunsum	5	3.36	No
Contubel	21	14.09	Yes
Cuntuba	33	22.15	Yes
Djabicunda	35	23.49	Yes
Ga tauda	4	2.68	No
Gambasse	3	2.01	No
Tantacosse	11	7.38	No
Total	149		

A total of 179 households were interviewed from 11th of November 2014 to 17th of March 2015 by a single enumerator. Respondents were asked if they were interested, in the particular SHS product, and their socio-economic information was collected. 149 households that exhibited an interest in the product were chosen to conduct the CE. Only lead decision makers were surveyed. Surveys were conducted in Creole, the local Portuguese language. Respondents were isolated prior to the survey.¹⁴

Following the CE, the respondent was asked a series of social capital questions. Questions on time preference to elicit the respondent's discount rate followed, before concluding the survey. A full survey can be found in the Appendix.

¹⁴ Due to an error in randomization 80 surveys had to be discarded. The numbers stated above are of those of the final sample used.

4.7 Econometric modelling framework

Results were initially estimated through the conditional logit model (Louviere & Hensher, 1983; McFadden, 1974), an extension of the multinomial logit model, as is common practice in literature (Abdullah & Mariel, 2010; MacKerron, Egerton, Gaskell, Parpia, & Mourato, 2009).

In a conditional logit model the probability that one alternative will be chosen over another can be expressed with the following equation where μ is a scale parameter assumed to be 1. The error terms are assumed to be independently and identically distributed with an extreme value term. This allows solving the model through a maximum likelihood estimation (a series of iterations seek a global maximum that would maximize the probability that the model reproduces all its observations).

$$P[(U_{in} > U_{jn} \forall i \neq j] = \frac{\exp(\mu V_{in})}{\sum \exp(\mu V_{jn})}$$

Initially, the simple log model focusing on the choice attributes was tested. Subsequently extended models were chosen including socio-economic attributes, trust indicators and latter discounting preferences.

The ratio of coefficients of two attributes, holding utility constant, is their marginal rate of substitution. Where a price attribute is included this ratio becomes the marginal WTP for changes in attributes:

$$WTP = -1 \left(\frac{\beta_{attribute}}{\beta_{price}} \right)$$

The conditional logit model however relies on a number of limiting assumptions, which if they don't hold, might lead to biased estimations, namely the independence of irrelevant alternatives and homogeneity of preferences. It has therefore been replaced by more sophisticated models (K. Train, 2003).

A mixed logit model was subsequently tested with the same variables, which through a likelihood ratio test proved to have a stronger fit. Here we report these results. Conditional logit results can be found in the Appendix.

Mixed logit models (also referred to as random parameters logit models -RPL) relax the stringent assumptions discussed for the conditional logit model. Error terms are allowed to correlate between alternatives (no reliance on independence of irrelevant alternatives) and across choice sets for the same individuals (taking account of the repeated choice data). Finally, the model allows to factor in heterogeneity of preferences (D. A. Hensher & Greene, 2003; K. E. Train, 2009).

The Mixed logit model allows the coefficients b to vary randomly across individuals. These coefficients can be divided into a population mean β and an unobserved individual deviation from that mean η_i , therefore the utility of individual n choosing alternative j can be expressed as:

$$U_{nj} = b_n x_{nj} + \varepsilon_{nj} = \beta_n x_{nj} + \eta_n x_{nj} + \varepsilon_{nj}$$

The residual error term ε_{nj} is assumed to be independently and identically distributed according to the extreme value form. The probability that individual n chooses alternative j is given by the following formula:

$$P_{nj} = \int \frac{\exp(b_n x_{nj})}{\sum_{j=1}^J \exp(b_n x_{nj})} f((\beta_n | \theta) d(\beta_n)$$

Where θ represents the parameters of the probability distribution of the b_n . The integral does not have a closed form and is calculated with simulation methods taking the average values over a large number of draws of b from a particular distribution θ . These figures are subsequently inserted into a simulated log likelihood function to which conventional maximization techniques are applied.

The model selected for this study specifies random normally distributed coefficients for all the product attributes, apart from the prices, which were estimated as fixed coefficients. This is a common practice in many CE applications using discrete choice models with random coefficients (Hensher, Shore, & Train, 2005; Train, 2003). All the interacted socio-economic variables were also estimated as fixed parameters as when they were modelled as random, their

standard deviations were found to be insignificant. Both mean and standard deviation parameters for the random coefficients are reported. Following a log likelihood ratio test all the estimated mixed logit models were found to have a significantly improved fit in comparison to the conditional logit estimations. This shows that the mixed logit model fits the data better (Campbell, Hutchinson, & Scarpa, 2009; Hall, Fiebig, King, Hossain, & Louviere, 2006; Revelt & Train, 1998). The software used throughout this study, unless otherwise stated, was Stata 14.

5. Results

5.1 Summary statistics

5.1.1 Demographic characteristics

Table 6 presents the main socio-economic characteristics of the respondents. The sample consists almost exclusively of male individuals, as in most cases the decision maker is male. The sample also predominantly consists of individuals with low schooling as only 2% has received secondary education, 27% has received primary education, 50% has only received religious schooling, and 20% has not received any schooling at all.

As far as employment is concerned the predominant majority of households (98%) are involved in some form of agricultural activity. Only 7% of households have a member that receives a stable salary. In an effort to further capture the seasonality of income, respondents were asked how much they suffer during the rainy season (in terms of economic hardship). 37% reported to experience ‘a lot of hardship’, 57% reported to experience ‘some hardship’ and only 5% reported to experience ‘no hardship at all’.

The big dependence of the country from help from abroad can be seen by the fact that 40% of those households sampled, receive remittances from abroad.

Finally, the nature of the extended households in Guinea-Bissau can be seen by the reported household size and the responses regarding family pressures to share money with other family members. 49% of households surveyed have 20 or more household members, and only 11% of respondents reported to not feel any pressure to share money with other members of their household.

TABLE 6 SUMMARY STATISTICS OF THE SAMPLE

Total households sampled	149	Ethnicity (%)	
Respondent male (%)	98.66	Fula	15.44
Schooling of respondent (%)		Mandinga	75.17
Never had any education	20.13	Balanta	1.34
Only religious education	50.34	Other	8.05
Primary education	27.52	Children in household (%)	77.85
Secondary education	2.01	Age of respondent (%)	
Superior education	0	20-29	4.03
Employment (%)		30-39	28.19
Agriculture	98.66	40-49	22.15
Fishing	16.11	50-59	25.50
Animals	91.28	60+	20.13
Large animals	12.75	Household size (%)	
Public employees	1.34	0-8	16.78
Private employees	6.71	9-13	16.78
Commerce	26.17	14-19	17.45
Household receiving fixed salary (%)	7.38	20-30	24.16
Remittances (%)	40.27	>30	24.83
Self-reported pressure to share money (%)		Self-reported financial hardship during the rainy season (%)	
Not at all	11.41	A lot of hardship	37.58
A little	75.84	Some hardship	57.05
A lot	12.75	No hardship at all	5.37

5.1.2 Trust for different actors

Guinea-Bissau is a country with a high degree of solidarity and social links that make up for the lack of well-functioning institutions. This solidarity can be seen in the high level of trust reported in Table 7 for people in the community and traditional leaders. These levels are lower for local institutions and NGOs, but are still high.

TABLE 7 SUMMARY STATISTICS ON SELF-REPORTED TRUST

	Trust a lot	Trust	Not trust nor distrust	Distrust	Distrust a lot
Trust the people in the community	44.30%	31.54 %	18.79 %	4.70%	0.67 %
Trust NGOs	24.16 %	47.65%	12.75 %	15.44%	
Trust traditional leaders	54.36 %	34.23 %	7.38 %	3.36%	0.67%
Trust local government	33.56 %	35.57 %	22.15 %	8.72%	

Two indicators of different measures of trust were created, based on the responses using the principal component analysis (PCA), which is a descriptive technique that summarizes variables that are correlated. The first indicator is a general level of trust (PC1) with larger levels expressing lower levels of trust. The second indicator represent the contrast between trusting local informal actors and external institutionalized actors (PC2) with larger levels, indicating higher levels of trust for informal local actors, in comparison to institutionalized external actors. More details about how these indicators were created can be found in the Appendix.

5.1.3 Income indicators

Nearly all the respondents use a combination of candles, flashlights and lamps powered with batteries, to meet their lighting needs (detailed information regarding energy use can be found in the Appendix).

Very few households receive fixed salaries or have a stable employment, therefore it is very difficult to elicit monthly household income. In this type of situations in developing countries it is very common to use income proxies in order to classify households according to their income (e.g. Takama et al., 2012). Based on the reality of the Bissau-Guinean society an income proxy was created based on the possession of energy durables. More precisely possession of TV and/or a generator was used as a proxy for income level, as better off families tend to possess at least one of the two (26% of our sample).

This proxy was chosen after the interviews and focus groups. These consultations revealed that the income indicator based on household characteristic (often used in developing country research) (e.g. Takama et al., 2012), is less robust amongst the different surveyed communities, in comparison to the possession of energy durables. Therefore, it was deemed appropriate to focus on the possession of energy durables as an income proxy.

Finally, 99% of respondents have seen a SHS before, although the percent that knows how a SHS works is much lower (38%) (Table 9). This is a good indication that respondents were familiar with the product during the valuation exercise, which is central to minimizing hypothetical bias.

TABLE 8 INCOME PROXY BASED ON POSSESSION OF DURABLES

Possession of Generator (%)	16.11
Possession of Television (%)	24.16
Possession of TV and/or of a generator (%)	26.53

TABLE 9 REPORTED KNOWLEDGE OF SHS

Seen a SHS before (%)	98.66
Knows how a SHS works (%)	
Yes	35.57
No	55.03
Not Sure	9.4

5.2 Determinants of lack of interest in the product

In total 30 out of 179 households reported they were not interested in the SHS under valuation. These households did not participate in the CE exercise. Table 10 reports the result of a binary logistic regression, which looks at the determinants of not being interested in purchasing the SHS. Results suggest that lack of interest in the product is largely driven by the limitations in the services offered from the specific SHS product. Possessing a TV is the only variable that is significantly and positively correlated with not wanting the product. This finding is also consistent with SHS literature, as limitations in uses is considered one of the bigger impediments to more SHS adoption, and television is one of the highest demanded applications (Nieuwenhout et al., 2001; Nieuwenhout et al., 2000; Urmee et al., 2009).

These results suggest that if the NGO chooses not to include a TV as a feature of the SHS it will lose many of its clients amongst the pool of those that are better able to pay. Since possession of a TV is an indication of being in a higher income level.

TABLE 10 DETERMINANTS OF NOT BEING INTERESTED IN THE SHS OFFERED

	Coefficient (std. err.)
Age of respondent	-0.01 (0.02)
Family size	-0.02 (0.02)
Household has children	0.26 (0.57)
Household receives a fixed salary	-0.18 (0.74)
Household receives remittances	0.23 (0.43)
Household possesses generator	0.73 (0.57)
Household possesses TV	1.18** (0.58)
Constant	-1.45 (0.95)
<i>Log likelihood</i>	-72.49
<i>N</i>	179
<i>Prob > chi2</i>	0.018

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Logistic regression with robust standard errors.

5.3 Mixed logit results

Table 11 provides a description and the coding of the main variables used in the model of delivery model preference.

TABLE 11 VARIABLES INCLUDED IN THE MODEL OF DELIVERY MODEL PREFERENCE

	Type	Description
CE Model Variables		
Price Upfront	Continuous	Price offered for upfront scheme (FCFA) scaled to 1/10,000
Price Credit	Continuous	Price offered for credit scheme (FCFA) scaled to 1/10,000
Price Rental	Continuous	Price offered for rental scheme (FCFA) scaled to 1/10,000
Upfront	Binary	Alternative specific constant 1= upfront scheme
Credit	Binary	Alternative Specific constant 1= credit scheme
Rental	Binary	Alternative Specific constant 1= rental scheme
Maintenance	Binary	1=consumer has the responsibility of maintenance
Respondent Characteristics		
Energy durables	Binary	1= respondent possesses generator or TV (income proxy)
Remittances	Binary	1= respondent receives remittances from abroad
PC1	Continuous	Principal component score indicating general level of trust (higher levels indicate lower levels of trust)
PC2	Continuous	Principal component score indicating contrast between trust for external actors and actors within the community (higher levels indicate higher trust for actors within the community)

Table 12 reports the mixed logit results of delivery model choice (Model A), and the mixed logit results of delivery model choice, interacted with socio-economic variables of the income proxy and receiving remittances (Model B and Model C). Prices were scaled in 1/10,000.

Model A results indicate that all the attributes of the product offered, are highly significant and their signs conform to expectations from theory. Both the signs of maintenance responsibilities and of prices are negative, as expected. Standard deviations of the random parameters are large and highly significant, which confirms that preferences for different delivery models are heterogeneous.

The model remains robust with the introduction of socio-economic variables of income indicator and receiving remittances, although these factors do not have a significant effect on all delivery models. The income proxy based on possession of energy durables has a positive significant effect on demand for upfront and credit payments, and a small positive but insignificant effect on the rental scheme. Receiving remittances from abroad has only a positive effect on demand for upfront payments. The effect is positive but insignificant for the credit scheme, and negative but insignificant for the rental scheme. The way this can be interpreted is that lump sum remittances from abroad can help facilitate high one-off payments.

TABLE 12 MIXED LOGIT MODEL OF DELIVERY MODEL CHOICE (MODEL A) INCLUDING INTERACTIONS WITH SOCIO-ECONOMIC ATTRIBUTES (MODEL B AND MODEL C)

	Model A Coefficient (std. err.)	Model A Standard Deviation (std. err.)	Model B Coefficient (std. err.)	Model B Standard Deviation (std. err.)	Model C Coefficient (std. err.)	Model C Standard Deviation (std. err.)
Upfront	4.80*** (1.01)	5.32*** (1.05)	3.00*** (1.04)	4.74*** (1.03)	3.05*** (1.03)	4.68*** (1.02)
Credit	7.10*** (1.07)	3.53*** (0.65)	5.86*** (0.96)	3.18*** (0.62)	6.13*** (0.94)	3.17*** (0.61)
Rental	5.53*** (0.85)	2.87*** (0.58)	5.38*** (0.87)	2.64*** (0.55)	5.31*** (0.81)	2.69*** (0.55)
Maintenance	-5.60*** (0.87)	2.24*** (0.71)	-5.46*** (0.85)	2.37*** (0.78)	-5.41*** (0.84)	2.33*** (0.76)
Price Upfront	-0.48*** (0.09)		-0.44*** (0.09)		-0.44*** (0.09)	
Price Credit	-0.32*** (0.05)		-0.31*** (0.05)		-0.3*** (0.05)	
Price Rental	-0.13*** (0.02)		-0.12*** (0.02)		-0.12*** (0.02)	
Energy durables*Upfront			2.79** (1.25)		2.59** (1.22)	
Energy durables*Credit			2.93*** (0.96)		2.82*** (0.92)	
Energy durables*Rental			0.85 (0.84)			
Remittances*Upf ront			1.96* (1.12)		1.89* (1.10)	
Remittances*Cre dit			0.71 (0.78)			
Remittances*Ren tal			-0.66 (0.71)			
<i>Log likelihood</i>	-435.78		-419.78		-421.32	
<i>Chi2</i>	148.06		127.72		130.52	
<i>Draws</i>	1000		1000		1000	
<i>Observations</i>	574		566		566	

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000. Random parameters assumed to follow normal distributions.

Table 13 presents mixed logit results of an extended model, using interactions with the two indicators expressing trust levels which are created through the method of principal component analysis (Model D). Model E includes other socio-economic variables. Low general trust levels have a significant negative effect on preference for credit and rental delivery models. The effect on the upfront scheme is positive, but small and insignificant. On the other hand, low levels of trust for formal actors, external to the community, and high levels of trust for informal actors embedded in the community, has a positive significant effect on the demand for rental and credit schemes. These results can therefore be interpreted as an indication that lower levels of trust of locally embedded actors specifically have a negative effect on demand for delivery models which entail monthly repayments. In other words, lack of trust renders individuals more hesitant to engage in contracts that require frequent repayments. This could be explained by the lack of a social structure to rely upon in case one is unable to repay. These results remain robust even after controlling for socio-economic factors (Model E).

Following a log likelihood ratio test, all the extended models reported have a significantly improved fit, in comparison to the basic model.

TABLE 13 MIXED LOGIT MODEL OF DELIVERY MODEL CHOICE INCLUDING INTERACTIONS WITH INDICATORS EXPRESSING RESPONDENTS' TRUST LEVELS (MODEL D) AND SOCIO-ECONOMIC VARIABLES (MODEL E)

	Model D Coefficient (std. err.)	Model D Standard Deviation (std. err.)	Model E Coefficient (std. err.)	Model E Standard Deviation (std. err.)
Upfront	4.80*** (1.03)	5.36*** (1.06)	3.01*** (1.06)	4.82*** (1.02)
Credit	6.9*** (0.99)	3.27*** (0.62)	5.96*** (0.88)	2.92*** (0.58)
Rental	5.52*** (0.81)	2.46*** (0.57)	5.36*** (0.79)	2.30*** (0.53)
Maintenance	-5.46*** (0.82)	2.09*** (0.69)	-5.34*** (0.80)	2.18*** (0.72)
Price Upfront	-0.48*** (0.09)		-0.44*** (0.08)	
Price Credit	-0.31*** (0.05)		-0.30*** (0.04)	
Price Rental	-0.13*** (0.02)		-0.12*** (0.02)	
PC1*Upfront	-0.06 (0.37)		0.05 (0.35)	
PC1*Credit	-0.8*** (0.29)		-0.80*** (0.27)	
PC1*Rental	-0.75*** (0.23)		-0.73*** (0.22)	
PC2 *Upfront	0.36 (0.57)		0.20 (0.54)	
PC2 *Credit	1.01** (0.45)		1.09** (0.43)	
PC2 *Rental	0.86** (0.36)		0.80** (0.35)	
Energy			2.67** (1.26)	
durables*Upfront				
Energy durables*Credit			3.03*** (0.89)	
Remittances*Upfront			1.95* (1.14)*	
<i>Log likelihood</i>	-422.26		-406.72	
<i>LRchi2</i>	143.74		125.97	
<i>Draws</i>	1000		1000	
<i>Observations</i>	574		566	

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000. Random parameters assumed to follow normal distributions.

5.4 Willingness to pay

Table 14 reports the mean WTP both for Model A and the extended Model C using the delta method. For the credit and the rental options, mean WTP is reported both as a total as well as a per month basis¹⁵.

The NGO plans to offer upfront and credit options only, with maintenance responsibilities and rental schemes without maintenance responsibilities on a total price of 100,000 FCFA for the upfront scheme and 4,000 FCFA per month for the credit and rental schemes. Therefore, only the mean WTP for the rental scheme without maintenance responsibilities (3,595 FCFA per month) is roughly comparable to the price proposed by the NGO (4,000 FCFA per month). This does not necessarily mean that the products in these prices are not viable. The NGO is planning to offer three different products, therefore only expecting to capture a part of the consumer basis with each product and delivery model.

¹⁵ To calculate monthly WTP, the total is divided by 24 for the credit option and by 120 for the rental option.

TABLE 14 WTP FOR THE DIFFERENT DELIVERY MODELS OF THE SHS USING THE POPULATION MEANS OF THE RANDOM PARAMETERS INCLUDING INTERACTIONS WITH SOCIO-ECONOMIC VARIABLES

	Model A Implicit price - FCFA (95%confidence Interval)	Model B Implicit price - FCFA (95%confidence Interval)
Upfront	99,416 (71,843 126,990)	69,535 (32,229 106,841)
Credit	224,243 total 9,343 per month (195,937.7 252,547.5)	201,593 total 8,400 per month (171,410 231,775)
Rental	431,372 total 3,595 per month (368,734.8 494,009.2)	430,497 total 3,587 per month (366,739 494,256)
Maintenance for Upfront	-116,058 (-152,465 -79,650)	-123,461 (-164,204 -82,717)
Maintenance for Credit	-177,146 total -7,381 per month (-216,315.8 -137,975.3)	-178,144 total -7,423 per month (-218,405 -137,883)
Maintenance for Rental	-436,957 total -3,641 per month (-544,257.2 -329,657.4)	-438,991 total -3,658 per month (-551,321.7 -326,659.8)
Energy durables*Upfront		59,154 (3,547 114,761)
Energy durables*Credit		92,871 total 3870 per month (36,841 148,901)
Remittances*Upf ront		43,036 (-5,646 91,719)

5.5 Market shares

Market shares were simulated based on the previous mixed logit estimations (Model A) for a range of prices and maintenance responsibilities. Initially the prices and maintenance responsibilities proposed by the collaborating NGO were used (Table 15). In this case the largest market share is captured by the rental scheme (49.9%) followed by the credit scheme (12.7%) and then the upfront scheme (7.4%). In addition, the simulation results indicate that with these prices and maintenance responsibilities 29.8% of the potential market is not captured at all. In the last row, the market shares estimated by the partnering NGO are higher for the upfront scheme and lower for the rental scheme. Overall, simulation results find higher total market shares (70%) than were estimated by the NGO (56%). However, it should be noted that these figures are not directly comparable as credit schemes were missing from the NGO's calculations, and our calculations are only based on the share of households expressing interest in the product.

TABLE 15 SIMULATED MARKET SHARES FOR THE DIFFERENT DELIVERY MODELS FOR PROPOSED PRICES AND MAINTENANCE RESPONSIBILITIES

	Upfront	Credit	Rental	No product
Price	100,000 FCFA	4,000 FCFA per month	4,000 FCFA per month	N/A
Maintenance	User	User	Company	N/A
Market shares	7.4%	12.7%	49.9%	29.8%
Market share estimated by TESE	17%		39%	

Table 16 describes a scenario where credit is offered without maintenance responsibilities for the user, and the monthly price doubles. In this case a significantly higher market share is captured overall. 5.6% of the market is captured by the upfront scheme, 41.5% by credit, 36.2% by rental and 16.5% of the market is not captured at all.

TABLE 16 SIMULATED MARKET SHARES FOR THE DIFFERENT DELIVERY MODELS FOR CHANGES IN THE CREDIT SCHEME COMPARED TO PROPOSED PRICES AND MAINTENANCE RESPONSIBILITIES

	Upfront	Credit	Rental	No product
Price	100,000 FCFA	8,000 FCFA per month	4,000 FCFA per month	N/A
Maintenance	User	Company	Company	N/A
Market shares	5.7%	41.5%	36.3%	16.5%

This effect becomes even larger when upfront schemes are also offered without maintenance responsibilities while their prices double (Table 17). Only 12.5% of the market remains not captured. The upfront scheme captures 18.9% of the market, the credit scheme 36.8% and the rental scheme 31.6%.

TABLE 17 SIMULATED MARKET SHARES FOR THE DIFFERENT DELIVERY MODELS FOR CHANGES IN THE CREDIT AND UPFRONT SCHEMES COMPARED TO PROPOSED PRICES AND MAINTENANCE RESPONSIBILITIES

	Upfront	Credit	Rental	No product
Price	200,000 FCFA	8,000 FCFA per month	4,000 FCFA per month	N/A
Maintenance	Company	Company	Company	N/A
Market shares	19%	36.8%	31.6%	12.6%

Finally, Table 18 simulates the effect of imposing maintenance responsibilities to the user for all delivery models. Market shares decline drastically. 59.2% of the market is not captured. The upfront scheme captures 10% of the market share, credit captures 18.11% of the market share and the rental scheme captures 12.5% of the market share even if offered in one fourth of the previous price.

Although, these last two simulations reported in Tables 17 and 18 are not realistic in terms of market prices and maintenance responsibilities, they are an interesting exercise to see

how preferences vary along the different repayment schemes when maintenance responsibilities remain constant.

TABLE 18 SIMULATED MARKET SHARES FOR THE DIFFERENT DELIVERY MODELS FOR CHANGES IN THE RENTAL SCHEME COMPARED TO PROPOSED PRICES AND MAINTENANCE RESPONSIBILITIES

	Upfront	Credit	Rental	No product
Price	100,000 FCFA	4,000 FCFA per month	1,000 FCFA per month	N/A
Maintenance	User	User	User	N/A
Market shares	10.1%	18.1%	12.5%	59.3%

5.6 Implicit discount rates

Table 19 illustrates the implicit discount rates computed from the estimated mean WTP (based on the delta method) for the different delivery models in Model A. The following formula was used:

$$WTP_{upfront} = WTP_{monthly} * \frac{1+r}{r} \left(1 - \frac{1}{(1+r)^{n+1}}\right)$$

¹⁶

Discount rates are very high. In addition, discount rates are not stable and they decline with the time horizon or in other words, when larger time intervals are considered (rental), which is consistent with hyperbolic discounting.

TABLE 19 IMPLICIT DISCOUNT RATES INFERRED FROM COMPARING MEAN WTP FOR UPFRONT AND CREDIT SCHEME AND UPFRONT AND RENTAL SCHEME

	Credit	Rental
Yearly discount rate	1.84	0.55
Monthly discount rate	0.09	0.04

¹⁶ r is the monthly discount rate and n the number of repayment months

Table 20 uses mean WTP estimates from Model C to compute implicit discounting amongst different socio-economic groups. Households possessing energy durables and receiving remittances have much lower discount rates than households with no energy durable possessions which receive no remittances. This holds for both time horizons (rental and credit) and is consistent with theoretical and empirical work, demonstrating that discount rates fall for higher income levels (see Frederick et al., 2002).

TABLE 20 IMPACT OF INCOME FACTORS ON IMPLICIT DISCOUNT RATES

	Credit	Rental
Household without energy durables and not receiving remittances		
Yearly discount rate		
Yearly discount rate	3.35	0.89
Monthly discount rate	0.13	0.05
Household with energy durables and receiving remittances		
Yearly discount rate		
Yearly discount rate	0.93	0.26
Monthly discount rate	0.056	0.019

5.7 Time preference questions

5.7.1 Responses to time preference questions

Table 21 reports the descriptive results of the time preference questions. 21% of respondents have a monthly discount rate that is lower than 25% for trade-offs now and 31% for trade-offs in a year from now. Mean monthly discount rates are 5.73 for trade-offs now and 5.47 for trade-offs in a year from now. In addition, 23% of the respondents are hyperbolic discounters (higher discount rates in the second stage of the time preference questions in comparison to the first) and 6% are more patient in the future (lower discount rates in the second stage of the time preference questions in comparison to the first).

TABLE 21 DESCRIPTIVE STATISTICS OF ANSWERS TO TIME PREFERENCE QUESTIONS

Discount rates	
Average discount rate now	5.73
Average discount rate in a year from now	5.47
Hyperbolic preferences	23.29 %
More patient in the future	6.16%
Discount rate (Now vs 1 month)	Percent of respondents
0.25	21.23
0.75	6.16
1.25	5.48
1.75	4.11
2.25	1.37
2.75	2.05
3.75	13.70
5.5	2.05
9	2.05
11	41.78
Discount rate (12 months vs 13 months)	Percent of respondents
0.25	33.10
0.75	8.28
1.25	3.45
1.75	2.07
3.75	6.90
5.5	0.69
9	2.76
11	42.76

Hyperbolic preferences: higher discount rates in the present than in the future. More patient in the future: lower discount rates in the present than in the future.

Studies conducted in developed countries find significantly lower rates. For example, Thaler, 1981 finds yearly discount rates to range from 1% to 345% for hypothetical choices, Coller & Williams, 1999 find discount rates for elicitation with real payments between 1 month to 3 months to range from 15%-25%.

Harrison, Lau, & Williams, 2002 also using actual payments find annual discount rates to be 28%. Andersen, Harrison, Lau, & Rutström, 2008 find an average annual discount rate of 10.1% when also controlling for risk preferences. In a developing country setting studies conducted also find lower discount rates. Bauer et al., 2012 find three-month discount rates in rural India to be 0.244 for current trade-offs, and 0.193 for future trade-offs in elicitations with real monetary rewards and controlling for risk preferences. Anderson, Dietz, Gordon, &

Klawitter, 2004 find monthly discount rates to range between 0.6% to 66.9% in Vietnam and Pender, 1996 find discount rates to range between from 0.26 to 1.19 in India.

The levels of absolute discount rates are not directly comparable across studies eliciting discount rates in the lab or the field as the time frames and the level of monetary gains or losses vary. For the objectives of this study what is important is to look at within sample variations (Bauer et al., 2012; Thaler, 1981).

In addition, the percentages of individuals exhibiting time preference reversals are comparable with other studies. Bauer et al., 2012 find the percent of individuals who exhibit hyperbolic preferences to be 33% and 9.6% to be patient now and impatient in the future. Ashraf et al., 2006 find 25.7% to exhibit hyperbolic preferences and 14.6% to be more patient in the future. Finally, Dupas & Robinson, 2013 find these numbers to be 16% and 18% respectively.

5.7.2 Discounting behaviour as a predictor of delivery model preference

Table 22 reports the mixed logit results of delivery model preference including interactions with discounting preferences. Overall, being impatient now (respondent exhibits discount rates larger than 25% for trade-offs now) has a significant negative effect on the demand for upfront and credit delivery models (albeit a larger effect for the upfront delivery model). This implies a correlation between the two expressions of discounting that retains its significance even after controlling for a range of socio-economic indicators including pressures to share money with other household members, schooling, age, household size, that have no significant effect overall. In addition, being a hyperbolic discounter has a significant positive effect on demand for credit schemes. These results show that rental schemes help address barriers to SHS adoption associated with high discount rates and credit schemes help address barriers to SHS adoption associated with self-control problems.

It could be argued that sophisticated hyperbolic discounters see credit as a commitment mechanism. Upfront payments require savings, and rental schemes indefinite repayments. Rental schemes entail less of a commitment as they can be terminated with no costs to users (in contrast in the credit scheme termination of repayment entails giving up the opportunity to own the system when all repayments are completed). This is in line with other findings in literature, however, it should be noted that these studies are finding an association between demand for commitment and hyperbolic discounting only for women (Ashraf et al., 2006; Dupas & Robinson, 2013, Bauer et al. 2012). Women were unfortunately not represented in our study.

An interesting implication of this last finding is that hyperbolic discounting in the case of implicit discounting, based on delivery method choice (discount rates declining with time horizon i.e. higher preference for rental schemes in comparison to credit) does not correlate with hyperbolic discounting measures based on the time preference questions.

However, it should be stressed that the effects of hyperbolic discounting are not robust in the conditional logit model (although signs and magnitude are retained) (see Appendix). In addition, in the mixed logit model, there is a positive effect, albeit not a significant one, for all other delivery models.

Finally, these results show that implicit discount rates calculated from trade-offs between delivery models for SHS are only partly driven by high discount rates, but also by income levels, trust for different actors and hyperbolic preferences.

TABLE 22 MIXED LOGIT MODEL OF DELIVERY MODEL CHOICE INCLUDING INTERACTIONS WITH ATTRIBUTES EXPRESSING RESPONDENTS' DISCOUNTING BEHAVIOUR (MODEL F) AND SOCIO-ECONOMIC VARIABLES (MODEL G)

	Model F Coefficient (std. err.)	Model F Standard Deviation (std. err.)	Model G Coefficient (std. err.)	Model G Standard Deviation (std. err.)
Upfront	7.34*** (1.63)	4.46*** (0.96)	4.15* (2.60)	4.61*** (1.01)
Credit	7.78*** (1.31)	3.31*** (0.65)	7.15*** (1.96)	2.91*** (0.61)
Rental	4.68*** (0.99)	2.76*** (0.57)	6.01*** (1.72)	2.29*** (0.54)
Maintenance	-5.34*** (0.92)	2.26** (1.05)	-5.55*** (0.86)	2.56*** (0.87)
Price Upfront	-0.48*** (0.09)		-0.47*** (0.09)	
Price Credit	-0.32*** (0.05)		-0.33*** (0.05)	
Price Rental	-0.12*** (0.02)		-0.12*** (0.02)	
Impatient now*Upfront	-3.66** (1.44)		-3.8** (1.54)	
Impatient now*Credit	-1.78* (1.03)		-1.75* (1.04)	
Impatient now*Rental	0.65 (0.9)		0.12 (0.88)	
Hyperbolic*Upfront	1.02 (1.31)		1.48 (1.44)	
Hyperbolic*Credit	1.79* (0.98)		1.98** (1.00)	
Hyperbolic*Rental	0.37 (0.87)		0.73 (0.83)	
Energy durables*Upfront			2.45* (1.43)	
Energy durables*Credit			3.13*** (1.08)	
Energy durables*Rental			1.30 (0.89)	
Remittances*Upfront			2.25* (1.22)	
Remittances*Credit			0.61 (0.82)	
Remittances*Rental			-0.86 (0.68)	
PC1* Upfront			-0.05 (0.34)	
PC1* Credit			-0.80*** (0.28)	
PC1* Rental			-0.75*** (0.24)	
PC2* Upfront			0.91 (0.60)	
PC2* Credit			1.09*** (0.48)	
PC2* Rental			0.94*** (0.38)	
<i>Log likelihood</i>	-419.68		-382.89	
<i>Chi2</i>	137.70		113.12	
<i>Draws</i>	1000		1000	
<i>Observations</i>	562		554	

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000. Random parameters assumed to follow normal distributions. Model G controls additionally for household size, age of respondent, schooling level of respondent, and whether the respondent is pressured to share money with other household members.

6. Conclusions

This study uses a choice experiment to measure ‘Willingness to Pay’ for a SHS, its different delivery models (upfront, credit and rental) and their attributes (repayments over time, maintenance responsibilities). Consumer preferences for delivery models correlate with excessive discounting, hyperbolic discounting, trust for different actors and income proxies. Finally, not being interested in the product was driven by the fact that TV was not one of its features.

More specifically, households with higher income exhibit higher demand for upfront and credit schemes, whereas individuals with high discount rates have a lower preference for upfront and credit schemes. In addition, there is some evidence that individuals exhibiting hyperbolic discounting have a higher preference for credit schemes. One explanation behind this is that credit provides a form of commitment. Finally, lower levels of self-reported trust for actors within the community lead to a lower preference for credit and rental schemes possibly because individuals feel less comfortable committing to monthly repayments. There is no evidence that intra-household pressures to share money affects delivery model choice.

These results add to the studies looking at upfront cost barriers for technology adoption of a number of beneficial technologies in developing countries (Duflo et al., 2011; Dupas & Robinson, 2013). So far no study has considered the case of SHS adoption, the impact of different delivery models in overcoming adoption barriers and their interaction with socio-economic, behavioural and social factors.

This study also informs the discounting elicitation literature that uses revealed preference methods to measure time preferences (e.g. Hausman, 1979; Revelt & Train, 1998). So far there hasn’t been a thorough investigation of the underlying determinants of implicit discount rates. The significant correlation between discounting behaviour, exhibited through preference for repayments over time, and discounting behaviour elicited separately by time preference questions, confirms that observed inter-temporal choices are driven by time preference only to a certain extent, as other factors affect inter-temporal decisions as well (hyperbolic discounting, social capital as expressed with trust for a number of actors).

Finally, implicit discount rates inferred from preferences for delivery models, managed to confirm certain priors regarding discounting anomalies that have been outlined in literature on discounting, namely excessive discounting, preference heterogeneity and time preference reversals (declining discount rates over time). These results underscore the replicability of these findings in different settings.

The findings of this valuation study, also fill a gap in literature concerning SHS delivery model provision which so far has only been descriptive, with no attempt to measure WTP and its determinants quantitatively. These findings can be extended further than the application on SHS as different types of services or goods could be provided in similar ways in developing countries.

As far as policy implications are concerned this study indicates that there is high demand for SHS in the context of rural Guinea-Bissau. This demand is however deterred from a number of income, behavioural and social factors that can be address with the right delivery model. Rental schemes capture the highest market shares, however as preference amongst consumers are heterogeneous it is advised to offer consumers the option to choose the delivery model that better suits their preferences. Finally, project implementers should consider the option of offering an additional product that includes a TV, which could potentially help capture a largest market share depending on the additional costs this would entail.

There are certain limitations in this study. We do not control for a number of possible mediating effects. For example, risk preferences and liquidity constraints were not taken into consideration, and they could be mediating income effects and discounting preferences. In addition, we are assuming that there no unobservable characteristics correlating with discounting and trust measures and with preferences for delivery models. Results remain robust to the inclusion of additional controls, however concerns about omitted variable bias cannot be eliminated.

Neighbourhood effects in the demand for SHS were not considered. Having a neighbour with a SHS can have both a positive (e.g. through knowledge spillovers) and a negative effect (though positive externalities of product services e.g. mobile charging) on product demand. The extent of which is difficult to estimate. In addition, as demonstrated in the summary statistics section, households in Guinea-Bissau tend to be large therefore it is not unlikely that there might be a demand for more than one system per household. This was not however considered as an option, as adding total costs would have been cognitively burdensome both for the respondents and the enumerator.

This survey looked at product valuation from the consumer's perspective. There are some issues crucial to the success of SHS projects that were not the focus of this study, but should be taken into consideration by project implementers. For example, several authors have found that resorting to cheap replacements, inability to understand maintenance requirements, and neglect of systems by consumers due to lack of ownership are common reasons for project failure (Nieuwenhout et al., 2001). Some confusion and misunderstanding about the delivery

models for programmes already in place was noted during the survey, interviews and focus groups. Project implementers should exercise caution when communicating to consumers, exactly what their chosen delivery model entails. Greater variety of delivery model increases market penetration and helps meet the preferences of a larger number of consumers, but also introduces a greater risk of confusion.

Due to limitations in the survey some attributes that could be relevant to consumer choice were not included, namely smaller upfront payments for credit and rental schemes (to increase user commitment), weekly instead of monthly repayments (to better replicate current energy spending patterns) and flexible repayments taking into consideration seasonality of income. These issues could be tested in a future study to further inform us on what considerations are behind preference for SHS delivery models in developing countries and how to better design SHS dissemination programs.

7. References

Abdullah, S., & Jeanty, P. W. (2011). Willingness to pay for renewable energy: Evidence from a contingent valuation survey in Kenya. *Renewable and Sustainable Energy Reviews*, 15(6), 2974-2983.

Abdullah, S., & Mariel, P. (2010). Choice experiment study on the willingness to pay to improve electricity services. *Energy Policy*, 38(8), 4570-4581.

Acker, R. H., & Kammen, D. M. (1996). The quiet (energy) revolution: analysing the dissemination of photovoltaic power systems in Kenya. *Energy Policy*, 24(1), 81-111.

Adamowicz, V. (1995). Alternative valuation techniques: A comparison and movement to a synthesis. *Environmental valuation new perspectives*, 144-159.

Adkins, E., Eapen, S., Kaluwile, F., Nair, G., & Modi, V. (2010). Off-grid energy services for the poor: introducing LED lighting in the Millennium Villages Project in Malawi. *Energy Policy*, 38(2), 1087-1097.

Allcott, H., & Greenstone, M. (2012). Is there an energy efficiency gap? *The Journal of Economic Perspectives*, 26(1), 3-28.

Allcott, H., & Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. *Review of economics and statistics*, 96(5), 779-795.

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3), 583-618.

Anderson, C. L., Dietz, M., Gordon, A., & Klawitter, M. (2004). Discount rates in Vietnam. *Economic Development and Cultural Change*, 52(4), 873-887.

Ashraf, N., Karlan, D., & Yin, W. (2006). Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines. *The Quarterly Journal of Economics*, 635-672.

Atkinson, G., & Mourato, S. (2008). Environmental cost-benefit analysis. *Annual review of environment and resources*, 33, 317-344.

Bartholomew, D. J., Steele, F., Galbraith, J., & Moustaki, I. (2008). *Analysis of multivariate social science data*: CRC press.

Bateman, I. J., & Langford, I. H. (1997). Non-users' willingness to pay for a National Park: an application and critique of the contingent valuation method. *Regional studies*, 31(6), 571-582.

Batley, S. L., Colbourne, D., Fleming, P., & Urwin, P. (2001). Citizen versus consumer: challenges in the UK green power market. *Energy Policy*, 29(6), 479-487.

Bauer, M., Chytilová, J., & Morduch, J. (2012). Behavioral foundations of microcredit: Experimental and survey evidence from rural India. *The American economic review*, 102(2), 1118-1139.

Benton, M., Meier, S., & Sprenger, C. (2007). Overborrowing and undersaving: Lessons and policy implications from research in behavioral economics. *Federal Reserve Bank of Boston Community Affairs Discussion Paper*, 7(4).

Bergmann, A., Hanley, N., & Wright, R. (2006). Valuing the attributes of renewable energy investments. *Energy Policy*, 34(9), 1004-1014.

Bradford, D., Courtemanche, C., Heutel, G., McAlvanah, P., & Ruhm, C. (2014). Time preferences and consumer behavior. *National Bureau of Economic Research*.

Busse, M. R., Knittel, C. R., & Zettelmeyer, F. (2013). Are consumers myopic? Evidence from new and used car purchases. *The American economic review*, 103(1), 220-256.

Campbell, D., Hutchinson, W. G., & Scarpa, R. (2009). Using choice experiments to explore the spatial distribution of willingness to pay for rural landscape improvements. *Environment and Planning A*, 41(1), 97-111.

Campbell, D., Hutchinson, W. G., & Scarpa, R. (2006). Lexicographic preferences in discrete choice experiments: Consequences on individual-specific willingness to pay estimates.

Carlsson, F., Frykblom, P., & Lagerkvist, C. J. (2005). Using cheap talk as a test of validity in choice experiments. *Economics letters*, 89(2), 147-152.

Carson, R. T., Flores, N. E., Martin, K. M., & Wright, J. L. (1996). Contingent valuation and revealed preference methodologies: comparing the estimates for quasi-public goods. *Land Economics*, 80-99.

Carson, R. T., Flores, N. E., & Meade, N. F. (2001). Contingent valuation: controversies and evidence. *Environmental and Resource Economics*, 19(2), 173-210.

Coller, M., & Williams, M. B. (1999). Eliciting individual discount rates. *Experimental Economics*, 2(2), 107-127.

Cummings, R. G., & Taylor, L. O. (1999). Unbiased value estimates for environmental goods: a cheap talk design for the contingent valuation method. *The American economic review*, 89(3), 649-665.

DeShazo, J., & Fermo, G. (2002). Designing choice sets for stated preference methods: the effects of complexity on choice consistency. *Journal of Environmental Economics and Management*, 44(1), 123-143.

Desvouges, W. H., Johnson, F. R., Dunford, R. W., Boyle, K. J., Hudson, S. P., & Wilson, K. N. (1992). *Measuring nonuse damages using contingent valuation: An experimental evaluation of accuracy* (Vol. 1992): Research Triangle Institute Research Triangle Park, NC.

Dreyfus, M. K., & Viscusi, W. K. (1995). Rates of time preference and consumer valuations of automobile safety and fuel efficiency. *The Journal of Law and Economics*, 38(1), 79-105.

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *The American economic review*, 101(6), 2350-2390.

Dupas, P., & Robinson, J. (2013). Why don't the poor save more? Evidence from health savings experiments. *The American economic review*, 103(4), 1138-1171.

Ferrini, S., & Scarpa, R. (2007). Designs with a priori information for nonmarket valuation with choice experiments: A Monte Carlo study. *Journal of environmental economics and management*, 53(3), 342-363.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2), 351-401.

Gately, D. (1980). Individual discount rates and the purchase and utilization of energy-using durables: Comment. *Bell Journal of Economics*, 11(1), 373-374.

Gerarden, T. D., Newell, R. G., & Stavins, R. N. (2015). Assessing the energy-efficiency gap. *National Bureau of Economic Research*.

Hall, J., Fiebig, D. G., King, M. T., Hossain, I., & Louviere, J. J. (2006). What influences participation in genetic carrier testing?: Results from a discrete choice experiment. *Journal of health economics*, 25(3), 520-537.

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice modelling approaches: a superior alternative for environmental valuation? *Journal of economic surveys*, 15(3), 435-462.

Harrison, G. W., Lau, M. I., & Williams, M. B. (2002). Estimating individual discount rates in Denmark: A field experiment. *The American economic review*, 92(5), 1606-1617.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 33-54.

Hensher, D., Shore, N., & Train, K. (2005). Households' willingness to pay for water service attributes. *Environmental and Resource Economics*, 32(4), 509-531.

Hensher, D. A., & Greene, W. H. (2003). The mixed logit model: the state of practice. *Transportation*, 30(2), 133-176.

Hess, S., Rose, J. M., & Polak, J. (2010). Non-trading, lexicographic and inconsistent behaviour in stated choice data. *Transportation Research Part D: Transport and Environment*, 15(7), 405-417.

Horowitz, J. K., & McConnell, K. E. (2002). A review of WTA/WTP studies. *Journal of Environmental Economics and Management*, 44(3), 426-447.

Jaccard, M., & Dennis, M. (2006). Estimating home energy decision parameters for a hybrid energy—economy policy model. *Environmental Modelling and Assessment*, 11(2), 91-100.

Johnson, M. W., & Bickel, W. K. (2002). Within-subject comparison of real and hypothetical money rewards in delay discounting. *Journal of the experimental analysis of behavior*, 77(2), 129-146.

Kahneman, D., & Knetsch, J. L. (1992). Valuing public goods: the purchase of moral satisfaction. *Journal of Environmental Economics and Management*, 22(1), 57-70.

Kim, S.-I., & Haab, T. C. (2009). Temporal insensitivity of willingness to pay and implied discount rates. *Resource and Energy Economics*, 31(2), 89-102.

Komatsu, S., Kaneko, S., Shrestha, R. M., & Ghosh, P. P. (2011). Nonincome factors behind the purchase decisions of solar home systems in rural Bangladesh. *Energy for Sustainable Development*, 15(3), 284-292.

Kovacs, K. F., & Larson, D. M. (2008). Identifying individual discount rates and valuing public open space with stated-preference models. *Land Economics*, 84(2), 209-224.

Krishna, A., & Shrader, E. (2000). Cross-cultural measures of social capital: a tool and results from India and Panama. *Social capital initiative working paper*, 21.

Lancaster, K. J. (1966). A new approach to consumer theory. *The journal of political economy*, 132-157.

List, J. A., & Gallet, C. A. (2001). What experimental protocol influence disparities between actual and hypothetical stated values? *Environmental and Resource Economics*, 20(3), 241-254.

Louviere, J. J., & Hensher, D. A. (1983). Using discrete choice models with experimental design data to forecast consumer demand for a unique cultural event. *Journal of Consumer Research*, 10(3), 348-361.

Lusk, J. L., & Norwood, F. B. (2005). Effect of experimental design on choice-based conjoint valuation estimates. *American Journal of Agricultural Economics*, 87(3), 771-785.

Lusk, J. L., & Schroeder, T. C. (2004). Are choice experiments incentive compatible? A test with quality differentiated beef steaks. *American Journal of Agricultural Economics*, 86(2), 467-482.

MacKerron, G. J., Egerton, C., Gaskell, C., Parpia, A., & Mourato, S. (2009). Willingness to pay for carbon offset certification and co-benefits among (high-) flying young adults in the UK. *Energy Policy*, 37(4), 1372-1381.

Madden, G. J., Begotka, A. M., Raiff, B. R., & Kastern, L. L. (2003). Delay discounting of real and hypothetical rewards. *Experimental and clinical psychopharmacology*, 11(2), 139.

Matsumoto, S., & Omata, Y. (2017). Consumer valuations of energy efficiency investments: The case of Vietnam's Air Conditioner market. *Journal of Cleaner Production*, 142, 4001-4010.

McEachern, M., & Hanson, S. (2008). Socio-geographic perception in the diffusion of innovation: solar energy technology in Sri Lanka. *Energy Policy*, 36(7), 2578-2590.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behaviour". In *Frontiers in Econometrics*, ed. P. Zarembka. (New York: Academic Press).

Metcalf, G. E., & Hassett, K. A. (1999). Measuring the energy savings from home improvement investments: evidence from monthly billing data. *The Review of Economics and Statistics*, 81(3), 516-528.

Min, J., Azevedo, I. L., Michalek, J., & de Bruin, W. B. (2014). Labelling energy cost on light bulbs lowers implicit discount rates. *Ecological Economics*, 97, 42-50.

Mitchell, R. C., & Carson, R. T. (1989). *Using surveys to value public goods: the contingent valuation method*: Resources for the Future.

Mjelde, J. W., Jin, Y. H., Lee, C.-K., Kim, T.-K., & Han, S.-Y. (2012). Development of a bias ratio to examine factors influencing hypothetical bias. *Journal of environmental management*, 95(1), 39-48.

Murphy, J. J., Allen, P. G., Stevens, T. H., & Weatherhead, D. (2005). A meta-analysis of hypothetical bias in stated preference valuation. *Environmental and Resource Economics*, 30(3), 313-325.

Narayan, D., & Pritchett, L. (1999). Cents and sociability: Household income and social capital in rural Tanzania. *Economic Development and Cultural Change*, 47(4), 871-897.

Newell, R. G., & Siikamäki, J. (2015). Individual time preferences and energy efficiency. *The American economic review*, 105(5), 196-200.

Newell, R. G., & Siikamäki, J. (2014). Nudging energy efficiency behavior: The role of information labels. *Journal of the Association of Environmental and Resource Economists*, 1(4), 555-598

Nieuwenhout, F., Van Dijk, A., Lasschuit, P., Van Roekel, G., Van Dijk, V., Hirsch, D., . . . Wade, H. (2001). Experience with solar home systems in developing countries: a review. *Progress in Photovoltaics: Research and Applications*, 9(6), 455-474.

Nieuwenhout, F., Van Dijk, A., Van Dijk, V., Hirsch, D., Lasschuit, P., Van Roekel, G., . . . Wade, H. (2000). Monitoring and evaluation of Solar Home Systems. Experiences with applications of solar PV for households in developing countries. *Netherlands Energy Research Foundation ECN*.

Nomura, N., & Akai, M. (2004). Willingness to pay for green electricity in Japan as estimated through contingent valuation method. *Applied Energy*, 78(4), 453-463.

Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural India. *Journal of development Economics*, 50(2), 257-296.

Rebane, K. L., & Barham, B. L. (2011). Knowledge and adoption of solar home systems in rural Nicaragua. *Energy Policy*, 39(6), 3064-3075.

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of economics and statistics*, 80(4), 647-657.

Saelensminde, K. (2002). The impact of choice inconsistencies in stated choice studies. *Environmental and Resource Economics*, 23(4), 403-420.

Sallee, J., West, S., & Fan, W. (2009). *Consumer valuation of fuel economy: a microdata approach*. Paper presented at the Proceedings of the National Tax Association Annual Conference on Taxation.

Takama, T., Tsephel, S., & Johnson, F. X. (2012). Evaluating the relative strength of product-specific factors in fuel switching and stove choice decisions in Ethiopia. A discrete choice model of household preferences for clean cooking alternatives. *Energy Economics*, 34(6), 1763-1773.

Tarozzi, A., Mahajan, A., Blackburn, B., Kopf, D., Krishnan, L., & Yoong, J. (2014). Micro-loans, insecticide-treated bednets, and malaria: evidence from a randomized controlled trial in Orissa, India. *The American economic review*, 104(7), 1909-1941.

TESE. (2010). Estudo de Caracterização Sócio Económica e do Consumo Energético de Bambadinca – Guiné-Bissau

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, 8(3), 201-207.

Train, K. (1985). Discount rates in consumers' energy-related decisions: A review of the literature. *Energy*, 10(12), 1243-1253.

Train, K. (2003). Discrete choice with simulation. In: Cambridge University Press, Cambridge.

Train, K. E. (2009). *Discrete choice methods with simulation*: Cambridge university press.

Urmee, T., Harries, D., & Schlapfer, A. (2009). Issues related to rural electrification using renewable energy in developing countries of Asia and Pacific. *Renewable Energy*, 34(2), 354-357.

Vischer, T., Dohmen, T., Falk, A., Huffman, D., Schupp, J., Sunde, U., & Wagner, G. G. (2013). Validating an ultra-short survey measure of patience. *Economics letters*, 120(2), 142-145.

Voravate, T., Barnes, D. F., & Bogach, V. S. (2000). *Assessing markets for renewable energy in rural areas of Northwestern China* (Vol. 23): World Bank Publications.

Wiser, R. H. (2007). Using contingent valuation to explore willingness to pay for renewable energy: a comparison of collective and voluntary payment vehicles. *Ecological economics*, 62(3), 419-432.

8. Appendix

8.1 Conditional logit estimations

TABLE 1 CONDITIONAL LOGIT MODEL OF DELIVERY MODEL CHOICE (MODEL A) INCLUDING INTERACTIONS WITH SOCIO-ECONOMIC ATTRIBUTES (MODEL B AND MODEL C)

	Model A Coefficient (std. err.)	Model B Coefficient (std. err.)	Model C Coefficient (std. err.)
Upfront	2.22*** (0.35)	1.55*** (0.42)	1.58*** (0.41)
Credit	3.15*** (0.34)	2.79*** (0.38)	2.97*** (0.36)
Rental	2.6*** (0.27)	2.67*** (0.31)	2.63*** (0.27)
Maintenance	-2.2*** (0.2)	-2.29*** (0.21)	-2.27*** (0.2)
Price Upfront	-0.17*** (0.03)	-0.17*** (0.03)	-0.17*** (0.03)
Price Credit	-0.14*** (0.02)	-0.15*** (0.02)	-0.14*** (0.02)
Price Rental	-0.06*** (0.01)	-0.06*** (0.01)	-0.06*** (0.01)
Energy		1.24*** (0.51)	1.16*** (0.48)
durables*Upfront		1.31*** (0.43)	1.28*** (0.36)
Energy durables*Credit		0.22 (0.43)	
Energy durables*Rental		0.48 (0.38)	
Remittances*Upfront		0.84* (0.48)	0.76* (0.43)
Remittances*Credit		-0.22 (0.37)	
Remittances*Rental			
<i>Log likelihood</i>	-509.81	-483.63	-486.58
<i>Wald chi2</i>	198.35	225.7	221.39
<i>Pseudo R2</i>	0.36	0.38	0.38
<i>Number of Respondents</i>	146	144	144
<i>Observations</i>	574	566	566

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000.

TABLE 2 CONDITIONAL LOGIT MODEL OF DELIVERY MODEL CHOICE INCLUDING INTERACTIONS WITH INDICATORS EXPRESSING RESPONDENTS' TRUST LEVELS (MODEL D) AND SOCIO-ECONOMIC VARIABLES (MODEL E)

	Model D	Model E
	Coefficient	Coefficient
	(std. err.)	(std. err.)
Upfront	2.33*** (0.36)	1.68*** (0.43)
Credit	3.22*** (0.34)	3.00*** (0.35)
Rental	2.69*** (0.26)	2.74*** (0.27)
Maintenance	-2.26*** (0.21)	-2.36*** (0.21)
Price Upfront	-0.18*** (0.03)	-0.18*** (0.03)
Price Credit	-0.14*** (0.02)	-0.15*** (0.02)
Price Rental	-0.06*** (0.01)	-0.06*** (0.01)
PC1*Upfront	-0.09 (0.15)	-0.06 (0.16)
PC1*Credit	-0.30** (0.12)	-0.32*** (0.12)
PC1*Rental	-0.37*** (0.11)	-0.37*** (0.11)
PC2 *Upfront	0.26 (0.29)	0.23 (0.33)
PC2 *Credit	0.42* (0.22)	0.47** (0.23)
PC2 *Rental	0.37** (0.19)	0.36* (0.19)
Energy durables*Upfront		1.21** (0.5)
Energy durables*Credit		1.38*** (0.39)
Remittances*Upfront		0.80* (0.44)
<i>Log likelihood</i>	-494.13	-469.71
<i>Wald chi2</i>	229.20	243.74
<i>Pseudo R2</i>	0.37	0.40
<i>Number of Respondents</i>	146	144
<i>Observations</i>	574	566

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000.

TABLE 3 CONDITIONAL LOGIT MODEL OF DELIVERY MODEL CHOICE INCLUDING INTERACTIONS WITH ATTRIBUTES EXPRESSING RESPONDENTS' DISCOUNTING BEHAVIOUR (MODEL F) AND SOCIO-ECONOMIC VARIABLES (MODEL G)

	Model F Coefficient (std. err.)	Model G Coefficient (std. err.)
Upfront	3.13*** (0.55)	1.95* (1.03)
Credit	3.73*** (0.48)	3.59*** (0.98)
Rental	2.49*** (0.48)	3.62*** (0.99)
Maintenance	-2.18*** (0.21)	-2.39*** (0.23)
Price Upfront	-0.17*** (0.03)	-0.19*** (0.03)
Price Credit	-0.15*** (0.02)	-0.16*** (0.03)
Price Rental	-0.06*** (0.01)	-0.06*** (0.01)
Impatient now*Upfront	-1.22** (0.55)	-1.28* (0.71)
Impatient now*Credit	-0.82* (0.43)	-0.62 (0.52)
Impatient now*Rental	0.08 (0.48)	-0.04 (0.54)
Hyperbolic*Upfront	0.05 (0.57)	0.27 (0.63)
Hyperbolic*Credit	0.59 (0.46)	0.62 (0.46)
Hyperbolic*Rental	0.06 (0.42)	0.03 (0.44)
Energy durables*Upfront		0.99* (0.59)
Energy durables*Credit		1.29** (0.54)
Energy durables*Rental		0.36 (0.49)
Remittances*Upfront		0.87* (0.47)
Remittances*Credit		0.43 (0.41)
Remittances*Rental		-0.36 (0.38)
PC1* Upfront		-0.02 (0.17)
PC1* Credit		-0.29** (0.12)
PC1* Rental		-0.37*** (0.12)
PC2* Upfront		0.32 (0.37)
PC2* Credit		0.41* (0.23)
PC2* Rental		0.40* (0.20)
<i>Log likelihood</i>	-488.53	-439.45
<i>Wald chi2</i>	182.95	304.43
<i>Pseudo R2</i>	0.37	0.42
<i>Number of Respondents</i>	143	141
<i>Observations</i>	562	554

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Prices scaled to 1/10,000. Model G controls additionally for household size, age of respondent, schooling level of respondent, and whether respondent is pressured to share money with other household members.

8.2 Principal component analysis and trust indicators

Principal component analysis (PCA) creates uncorrelated variables, the principal components, which are linear combinations of the original variables they represent. This method allows us to represent correlated variables with one variable, the principal component (which contains most of the information of the original variables), and to explore patterns of relationships between them. PCA is often used to summarize correlated variables and create indicators (Bartholomew, Steele, Galbraith, & Moustaki, 2008).

More specifically, for P observed variables x_i ($1 = 1, 2, 3, \dots, p$) measured for each unit, which are correlated with each other with a total variance:

$$\text{var}(x_1) = \text{var}(x_2) + \dots + \text{var}(x_p)$$

The principal components y_j ($j = 1, 2, \dots, p$) are linear combinations of the original variables. They are derived from the eigenvalue decomposition of the correlation (or covariance matrix of x_1, \dots, x_p). $\text{var}(x_j)$ is the j th eigenvalue and $(a_{1j}, a_{2j}, \dots, a_{pj})$ the corresponding eigenvector.

$$\begin{aligned} y_1 &= a_{11}x_1 + a_{21}x_2 + \dots + a_{p1}x_p \\ y_2 &= a_{12}x_1 + a_{22}x_2 + \dots + a_{p2}x_p \end{aligned}$$

.

$$y_3 = a_{13}x_1 + a_{23}x_2 + \dots + a_{p3}x_p$$

Where the following constraints apply:

$$\sum_{i=1}^p a_{ij}^2 = 1 \quad (j = 1, 2, \dots, p)$$

$$\sum_{i=1}^p a_{ij} a_{ik} = 0 \quad (j \neq k; j = 1, \dots, p; k = 1, \dots, p)$$

$$\sum_{j=1}^p \text{var}(y_j) = \sum_{i=1}^p \text{var}(x_i)$$

Principal components are derived and listed in order of decreasing variance.

The four variables ‘Trust people in the community’, ‘Trust NGOs’, ‘Trust traditional leaders’ and ‘Trust local government’ were assumed to be continuous in the 5-point scale. Larger

numbers indicated smaller amounts of trust. Table 4 indicates the eigenvalues and proportion of variance explained by the principal components that were created. Only the first two components were chosen for further analysis based on the prevalent rule of thumb (more than 70% of total variation is explained) (Bartholomew et al., 2008).

TABLE 4 PRINCIPAL COMPONENTS EIGENVALUES AND EXPLAINED PROPORTIONS

	Eigenvalue	Proportion
Component1	2.19	0.55
Component2	0.83	0.21
Component3	0.54	0.13
Component4	0.44	0.11

The principal component loadings derived for the first two components are presented in Table 5.

TABLE 5 PRINCIPAL COMPONENT LOADINGS

	Component 1	Component 2
Trust people in the community	0.68	-0.61
Trust NGOs	0.68	0.58
Trust traditional leaders	0.82	-0.22
Trust local government	0.78	0.27

The first component loadings are large and positive. This first component can be interpreted as a general measure of trust. The second component loadings are positive for trust in NGOs and local governments, and negative for people in the community and traditional leaders. This second component can be interpreted as a measure of the contrast between trust for local informal actors embedded in the community and trust for more formal actors outside the community. The second component is driven mostly by trust for people in the community and trust for NGOs, as component loadings are smaller for traditional leaders and local governments.

A component score was calculated for every individual using the component loadings as weights. The first score indicates the general level of trust (PC1) with larger levels expressing lower levels of trust. The second score indicates the contrast between trusting local informal actors and external institutionalized actors (PC2) with larger levels, indicating higher levels of trust for informal local actors, in comparison to institutionalized external actors.

8.3 Products proposed

	Low income families	Medium/ upper income group	Businesses
Wattage	0.5	20	170
Equipment	1 light, 1 mobile charger	4 lights, 1 Fan, 1 Radio, 1 mobile charger	4 lights, 1 fridge, 1 mobile charger
Price	30 USD	195 USD (upfront) 8 per USD per month (rental)	77 USD
Delivery models offered	Upfront	Upfront Rental	Rental
Market shares	44%	17% (upfront) 39% (rental)	0.5%

Information adopted from TESE 'Lojas Sta Claro' project proposal

8.4 Summary statistics of reported energy use

Around 2% report to actively use generators and 1% possess a normal sized PV (another 2% report to have a small panel which usually serves to power one light or charge a mobile phone). As far as cooking is concerned almost everyone uses wood for their cooking needs (98%). Current average household energy expenditure amounts to 9,700 FCFA, which is more than double the amount proposed for the monthly repayments in the credit and rental schemes (see Table 6).

When it comes to energy using equipment 94% of the respondents have mobile phones and 92% of them pay to charge them. 81% own radios, but only 5% own fans. 24% of respondents own a TV and 16% a generator.

TABLE 6 SUMMARY STATISTICS OF REPORTED ENERGY USE

Lighting	
Private Generator (%)	2.68
Candles (%)	65.10
Flash light (%)	94.63
Lamp with batteries (%)	85.91
Other similar to a lamp with batteries (%)	4.03
Regular Panel (%)	1.34
Small Panel (%)	2.01
Cooking	
Wood (%)	98.66
Coal (%)	0.67
Both wood and coal (%)	0.67
Energy Costs	
Average monthly expenditures for energy per household (FCFA)	9,700
Mobile phones	
Has mobile phone (%)	93.96
Pays to charge (%)	91.84
Other equipment	
Radios (%)	81.21
Television (%)	24.16
Generator (%)	16.11
Fan (%)	5.37
Fridge (%)	2.68
Computer (%)	1.34
Cable TV (%)	7.38

8.5 Maps of surveyed communities



8.6 Survey example

1. Introduction

Note to interviewer: Ask: ‘Who makes the financial decisions and decisions regarding the purchase of energy products in this household? Can I talk to this person?’. If not available, ask: ‘When can I come back to talk to that person?’. After you have established who to talk to, communicate the following information:

‘We are conducting a survey in your community that is part of a research initiative carried out by a PhD student at the London School of Economics and Political Science, a university in London, in partnership with ‘TESE’ an NGO working in Guinea-Bissau on infrastructural projects, including energy. The purpose of the questionnaire is to study the potential use of solar energy in your community.’

We have randomly chosen some of the households in your community and other communities in the region to participate in this survey, and your household is amongst the ones selected. If you agree to participate we will ask you to make some hypothetical choices regarding the purchase of solar energy and you will also be asked questions about your way of life, the kind of energy that you consume and your opinion about your community. These questions should take around an hour and a half to complete.

Your answers will be strictly confidential and will not be shared with anyone else. Answers will only be used anonymously for research purposes.

Participation is voluntary and you can refuse to participate without providing any explanation and without any consequences. If you agree to participate in the survey you have the right to stop whenever you want.

Your participation is very important to us. We will use the information you and other families give us to understand your preferences, and to design better solar products and delivery methods for a better future.

Do you have any questions? **May I continue interviewing you?**

It is very important that you give honest answers, not to over or under state the answers, because if the information we collect is not true, the outputs of the survey will not be beneficial to your community or Guinea-Bissau.'

(Note to interviewer: Isolate the respondent before beginning the interview).

<u>Note to interviewer:</u> are you speaking with the person who makes the financial decisions and decisions regarding the purchase of energy products in this household?	Yes No Other. Specify_____
Name of community	
What is your Mobile number? (<u>Note to interviewer:</u> After you ask for the mobile number, inform the respondent that the survey supervisor might be calling just to check if the survey was conducted properly).	
What is your name?	
What is the gender of the respondent?	Female Male
What is your age? (<u>Note to interviewer:</u> If they don't know their age or if they seem to be giving you the wrong answer take a note of the age they seem to be. As a clue, ask them what is the age of their eldest son).	
What is your education level?	No schooling Primary schooling Secondary schooling Superior schooling Other. Specify_____
Are you the head of the household?	Yes No
If 'No' what is the gender of the head of the household?	Female Male

2. Socio-economic questions

2.1 General socio-economic questions

Note to interviewer: Start this section by saying: 'I will begin by asking you a few questions on the demographic and socio-economic characteristics of your family, your activities the house where they live in and the things you possess.'

<p>How many people live in this household including you? By household I mean all individuals who normally live and eat their meals together in this household and share their expenses.</p> <p><u>(Note to interviewer:</u> To make sure we get the right response make sure you have a short conversation about what the relationship is of each member to the respondent. Example: Begin by asking who else lives here).</p>	
<p>What is the ethnicity of the household?</p>	<p>Fula Mandinga Balanta Beafada Papel Cabo-verdiana Other. Specify _____</p>
<p>How many children do you have in your household?</p>	
<p>How many years has your household lived in this community?</p>	
<p>What is the principal economic activity of your household?</p> <p><u>(Note to interviewer:</u> you can note more than one)</p>	<p>Public servants. Specify _____ Private employees. Specify _____ Services/ Commerce. Specify _____ Agriculture. Specify _____ Fishing. Specify _____ Animals. Specify _____ Other. Specify _____</p>
<p>Does any member of the family receive a fixed salary?</p>	<p>Yes No</p>
<p>Is your household negatively affected during the months when there is less availability of income in the community? (August, September, October)</p>	<p>Not at all A little bit A lot</p>

Does your household receive money from abroad?	Yes No
When you have money available are you pressured to share it with others in your household?	Not at all A little bit A lot
When you have money available are you pressured to share it with others outside your household?	Not at all A little bit A lot

2.2 Energy use questions

Note to interviewer: Start this section by saying: 'Now I would like to ask some questions concerning the use of energy in your household.'

What is the main source of lighting used in your household?	Private provider Generator Candles Flashlights Battery powered lamps Other. Specify_____
What is the main source of cooking used in your household?	Firewood Coal Other. Specify_____
Do you have mobile phones in your household?	Yes No
How many mobile phones does the household have?	
Where do you charge them?	At home Neighbour Store inside the community Store outside the community Other. Specify_____
Do you pay to charge them? (<u>Note to interviewer:</u> If 'No' go to the next section)	Yes No
How much do you pay to charge one?	
Do you have radios in your household?	Yes No
How many radios do you have?	
How do these radios work?	Generator

	Private provider Disposable batteries Rechargeable batteries Other. Specify _____
Do you have a generator in your household?	Yes No
Do you have a TV in your household?	Yes No
Do you have a fan in your household?	Yes No
Do you have a fridge in your household?	Yes No
Do you have a computer in your household?	Yes No
Do you have a satellite dish in your household?	Yes No

2.3 Expenditures

What is your family's expenditure (FCFA) at the moment?: (<u>Note to interviewer:</u> start by asking about daily expenses)	
Food	Per day _____ Per week _____ Per month _____ Other. Specify _____
Water	Per day _____ Per week _____ Per month _____ Other. Specify _____
Energy	Per day _____ Per week _____ Per month _____ Other. Specify _____
Education	Per day _____ Per week _____ Per month _____ Other. Specify _____

3. Valuation exercise

3.1 Demonstration of SHS

Have you seen a solar home system before?	Yes No Not sure Other. Specify _____
Do you know how a solar home system works?	Yes No Not sure Other. Specify _____

Note to interviewer: Introduce by saying: ‘now I will introduce to you a solar home product and afterwards ask you some hypothetical questions about purchasing it. Please remember that we are not selling anything to you yet, we are just asking questions to investigate your preferences’

Note to interviewer: show the cards with the pictures and explain:

‘This solar system has 4 lights and a plug to charge your mobile phone. It also allows you to use a radio and a fan. This is the only equipment you can use. For example, you cannot use a television or a refrigerator. This is the panel and this is the battery. You can use the lamps 7 hours per day and the radio, the fan and the charger a few hours a day depending on the use of each. The panel needs to be installed on your roof to create and store electricity from the sun during the day. These are the lamps which you can hang from the ceiling. The lighting quality of each lamp is equivalent to that of 16 candles. And this is where you can plug in your mobile charger to charge your phone, your fan and your radio. This is the battery you use when there is no more light and it stores electricity generated by the panel. The battery must be kept inside your house. This product is expected to last for 10 years but every now and then the battery, the lights and other equipment need to be changed.

Following the demonstration: Do you have any questions?’

In principle are you interested in purchasing this system:	Yes No Maybe
If ‘No’ why?	The product is too basic I need it to have more functions (extra lights, fridge, TV, etc.) The product is too elaborate I don’t need all those functions I want to decide the functions myself

	<p>I want to be able to share some of the functions with other families</p> <p>Not enough functioning hours</p> <p>I am satisfied with my current energy situation</p> <p>I don't think I will be able to afford it</p> <p>Other. Specify _____</p>
(Note to interviewer: if 'No' skip the choice experiment unless they state as a reason that they might not be able to afford it).	
If 'Yes' who will be paying:	<p>Respondent</p> <p>Other. Specify _____</p>

3.2 Attribute description

3.2.1 Repayment schedules

'If you are interested there are three different ways to acquire this solar system:

- 1) Upfront payment: You can purchase the system upfront where you will be asked to pay the whole amount right away to acquire the system. Then you can use the system throughout its lifetime, estimated to be 10 years.
- 2) Credit: You can acquire the system with credit, and for repayment you will need to pay a certain amount every month for the next two years. Then you can use the system throughout its lifetime, estimated to be 10 years.
- 3) Rental (Fee for service): Finally, you can rent the system. In this case, you must pay a certain amount every month for the length that you use the system and this is a maximum of 10 years, which is the expected lifetime of the panel.

In the case of credit and rent, the monthly repayments will be received in the beginning of every month by a representative of the company who will come to your house. If you are unable to meet repayments, the service will be paused until you start repaying again. If you cannot pay after a month, the system will be taken from you.'

These payment methods are symbolised with the following symbols.

(Note to interviewer: show picture card and explain what each symbol means)

‘Under the symbol that demonstrates the payment method a corresponding price will be listed.’

(Note to interviewer: explain the example cards that follow).

Finally, this symbol demonstrates the total costs of the different payment methods by adding up monthly repayments.

Note to interviewer: show picture card and explain what the total costs symbol means).

(Note to interviewer: explain the example cards that follow):

3.2.2 Maintenance responsibilities

‘Finally, solar home systems require some maintenance, which consists of cleaning the panel once a month but also repairing the system if something breaks, replacing different parts which might need replacing. The parts that usually need replacement are lamps, fuses and batteries. Lamps cost between 1000 and 2000 FCFA and fuses cost 600 FCFA each to replace. The lamps and the fuses need to be replaced every 8 years. The battery needs to be replaced every 4 years depending on the system being used properly and costs 43,300 FCFA. Other equipment is not expected to need replacement during the lifetime of the system, but equipment can always break or stop working unexpectedly.

The following symbols show what type of maintenance the user is responsible for; the rest is the responsibility of the company.

(Note to interviewer: show picture card and explain what each symbol means).

1. The maintenance responsibility of the user is to only clean the panel once every month. All repairs and replacements are the responsibility of the company.
2. The maintenance responsibility of the user is to clean the panel and to be responsible for all replacements and all possible repairs (including replacements of batteries, lamps and fuses).'

3.3 Choice card presentation

'We are now going to show you some choice cards. Each one presents three different options of acquiring this solar product in terms of prices, repayment methods and maintenance responsibilities. We will ask you to select the option you like the best. There is always a fourth option of not purchasing the product at all, if you do not wish to.'

We will show 4 choice cards and you will choose one of them. The first column will always present the option of purchasing the product with a one-off upfront payment. The second column will present the option to purchase the product with credit, and the third column will always present the option of acquiring the product with a rental scheme. However, levels of the prices and the maintenance responsibilities will always vary randomly. Others in the community might be presented with different cards. Your fourth option will be to not purchase the system at all.

When you make your choices please remember to be honest in your answers. Please treat this exercise as an actual purchase and keep in mind your budget limitations. Remember that your family's money will need to pay for other things like food, health, water, education, phone credit and clothes.

If you do not give us honest answers we will not be able to understand your preferences and how to make our design of the products better. Keep in mind also that your answers will not be able to influence the way that our products will be offered to you in terms of price levels, maintenance responsibilities and repayment schedules.'

3.4 Valuation questions

Note to interviewer: introduce each choice card the following way:

‘Imagine that a company offered you one of these three options to acquire the abovementioned solar home system’.

(Note to the interviewer: explain the choices, don’t forget to mention the choice of not buying anything).

(Note to the interviewer: make sure to make the respondent understand that these are the **only 3** options available).

Which would you choose from the following choices?	A: Upfront B: Credit C: Rental D: Nothing
--	--

3.5 Follow up questions (for respondent)

(Note to interviewer: ask the following questions to the respondent after each choice. Make sure to customize your questions in relation to their choice each time)

Are you sure your answer was realistic?	
Don’t you mind?	Doing all the maintenance yourself? Paying a rental fee for the next 10 years? Paying everything upfront? Repaying monthly for two years (in the case of credit)?
Do you have the money to?	Meet the upfront payment that is required? Pay the monthly instalments required?
Would you buy this product if it was offered to you now?	

3.6 Follow up questions (for interviewer)

(Note to interviewer: answer the following questions yourself after the choice experiment is over).

Did the respondent understand the choice card exercise?	Yes No Other. Specify _____
Did someone else choose for them?	Yes No Other. Specify _____
Did the respondent start losing attention at some point in the choice card demonstration?	Yes No Other. Specify _____
If 'Yes' which card was that?	1 2 3 4
Did the respondent choose randomly?	Yes No Other. Specify _____
Were the responses realistic?	Yes No Other. Specify _____

4. Trust questions

Note to interviewer: Introduce by saying: 'In every community some people get along and trust each other, while others do not. Now I want to ask you how much you trust different types of people'.

How much do you trust people from your community?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust NGOs?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust traditional village leaders?	Trust a lot Trust

	Neither trust nor distrust Distrust Distrust a lot
How much do you trust local government officials?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot

5. Time preference questions

Note to interviewer: Introduce by saying: ‘In conclusion I will ask you to answer some hypothetical questions regarding your preferences for receiving money at different times’:

5.1 Current trade-offs

If someone offered you a guaranteed 1,000 FCFA today, or 1,500 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(Note to interviewer: Continue asking, only if answer above is ‘Today’, otherwise stop and move to the following page). If someone offered you a guaranteed 1,000 FCFA today, or 2,000 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(Note to interviewer: Continue asking only if answer above is ‘Today’, otherwise stop and move to the following page). If someone offered you a guaranteed 1,000 FCFA today, or 2,500 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(Note to interviewer: Continue asking only if answer above is ‘Today’, otherwise stop and move to the following page). If someone offered you a guaranteed 1,000 FCFA today, or 3,000 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(Note to interviewer: Continue asking only if answer above is ‘Today’, otherwise stop and move to the following page). If someone offered you a guaranteed 1,000 FCFA today, or 3,500 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(Note to interviewer: Continue asking only if answer above is ‘Today’, otherwise stop and move to the following page). If someone offered you a guaranteed 1,000 FCFA today, or 4,000 FCFA guaranteed in 1 month, what would you prefer?	Today In a month

If someone offered you a guaranteed 1,000 FCFA today, or 4,500 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today', otherwise stop and move to the following page).	Today In a month
If someone offered you a guaranteed 1,000 FCFA today, or 5,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today', otherwise stop and move to the following page).	Today In a month
If someone offered you a guaranteed 1,000 FCFA today, or 8,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today', otherwise stop and move to the following page).	Today In a month
If someone offered you a guaranteed 1,000 FCFA today, or 12,000 FCFA guaranteed in 1 month, what would you prefer?	

5.2 Future trade-offs

If someone offered you a guaranteed 1,000 FCFA in 12 months, or 1,500 FCFA guaranteed in 13 months what would you prefer?	12 months 13 months
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 2,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 2,500 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months

If someone offered you a guaranteed 1,000 FCFA in 12 months, or 3,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 3,500 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 4,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 4,500 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 5,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 8,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months', otherwise stop and conclude the interview).	12 months 13 months
If someone offered you a guaranteed 1,000 FCFA in 12 months, or 12,000 FCFA guaranteed in 13 months what would you prefer?	

Chapter 3

An assessment of the determinants to connect to a solar hybrid mini-grid in Guinea-Bissau: the role of social capital

Abstract

This study explores the main determinants of the decision to connect to a solar hybrid mini-grid in Bambadinca, a semi-urban community in Guinea-Bissau, with a focus on the role of social capital, as expressed in trust for one's neighbours, in facilitating connections through the informal expansion of the grid. There is some evidence that social capital, as expressed in trust for one's neighbours, has a positive effect on the informal expansion of the grid, whereby households use their neighbours' infrastructure to connect to the service and reduce their upfront costs of connection. It has been possible to isolate this effect as, unlike other peer effects, it only becomes relevant for households that are farther away from the main grid. Results also indicate that the connection decision is driven by standard socio-economic variables and namely prior use of electricity, possession of electricity consuming appliances and income levels as well as upfront connection costs. Social capital as expressed with trust for a number of actors in the community and variables reflecting a households' integration in the community are not found to be affecting the connection decision.

1. Introduction

Mini-grids are designed to provide centralised electricity at the community level, which is then distributed to the users through a grid (World Energy Outlook, 2011). The technology used (diesel, renewable, or hybrid) and the installed capacity, define the type and size of activities that can be supported. Overall, mini-grids operate with higher loads than other isolated off-grid technologies that deliver electricity at the household level (e.g. solar home systems). In addition, mini-grids usually run in alternating current, which allows for the use of a larger variety of appliances, and support more income generating activities (see Rolland & Glania, 2011 for a description).

Mini-grids address a number of barriers to electrification both from the supply and demand side and are therefore seen as a promising solution to energy access problems in developing countries (World Energy Outlook, 2011). From the supply side they offer an alternative to grid expansion when the latter is not financially or technically feasible. From the demand side, social dynamics within the community can be harnessed in order to ensure repayments, avoid corruption, render the technology more inclusive and safeguard system reliability (Rolland & Glania, 2011). By design, mini-grids are embedded and often managed by the community, thus they have a unique ability to draw from and shape community dynamics. Therefore, mini-grids are an ideal subject for a study on the interplay of social dynamics and how they can pose as barriers and drivers to electrification.

A number of experimental and non-experimental studies have looked at the role of peer effects in technology adoption in developing countries. These applications are mainly on agriculture (Bandiera & Rasul, 2006; Conley & Udry, 2010; Isham, 2002), but there are also studies focusing on health (Kremer & Miguel, 2007), water (Devoto, Duflo, Dupas, Parienté, & Pons, 2012) and energy (Barron & Torero, 2015; Bernard & Torero, 2015; Adrianzén, 2014). Most studies attribute the presence of peer effects to learning or imitation effects, by rejecting other potential channels through observations, the use of secondary data and result interpretation (Bandiera & Rasul, 2006; Bernard & Torero, 2015; Adrianzén, 2014). The conditions under which diffusion is taking place through constraint interactions, when one's adoption decisions incurs externalities on the adoption constraints of others, has been less studied despite their highlighted significance (Bernard & Torero, 2015; Lee, Miguel, & Wolfram, 2016).

In the case of electrification connecting households can affect other household's connection decisions through two types of positive externalities.

One is by lowering costs associated with the service for others. One such instance is when the upfront connection costs for neighbouring households are lowered as the grid is brought closer to them when a neighbour connects to electricity.

These households now have the opportunity to connect through the grid infrastructure already expanded by their neighbour. This can lead to the informal expansion of the grid, whereby neighbours come into an agreement to share each others connecting infrastructure and therefore the ‘variable costs’ of connections associated with the extension of the grid (cables, poles, wires). This becomes more relevant for households that are farther away from the main grid. One related phenomenon is when households share the ‘fixed costs’ of connections by connecting to the service of a neighbour informally (‘spider webs’) (Bernard & Torero, 2015).

The second externality appears when households that are not electrified, can use the electricity provided by connected households. This can occur both directly (using a neighbour’s service to power appliances, or go to the neighbour to watch TV) and indirectly (neighbourhood is less dark at night) (Lee et al., 2016). It should be noted that although the first externality is expected to affect households’ adoption decision positively, the second externality affects households’ decisions to connect negatively.

This chapter investigates how social capital at the neighbourhood level as measured in self-reported trust for one’s neighbour can affect the likelihood of connection to a community solar hybrid mini-grid in rural Guinea-Bissau through encouraging the informal expansion of the grid infrastructure. This refers to only sharing grid infrastructure, and not informal connections as monitoring was in place to avoid illegal connections. Trust for one’s neighbour is expected to play a positive role in the informal expansion of the grid as neighbours need to come to an agreement about how to share the costs or to allow each other to use their infrastructure. Therefore, the level of trust underpinning their relationship can affect the success of this process.

The potential effect of constraint interactions through the informal expansion of the grid can have important implications for electrification since high upfront connection costs are found to constitute one of the most important barriers to electrification (Bernard & Torero, 2015; Lee et al., 2016). Therefore, a better understanding of the environment under which it can materialise is warranted.

This exercise is also aiming to inform the literature that looks at the channels through which trust as a measure of social capital can enhance technology adoption. As mentioned in Chapter 1 trust can only capture social capital partially. Either seen as a one of its components ((Putnam 1995: 67 in (Krishna & Shrader, 2000)) or as an outcome of social capital (Woolcock,

1998). Despite this limitation a number of scholars have used self-reported trust as an indicator of social capital to explain a broad range of economic phenomena including technology adoption (e.g. Adrianzén, 2014; McEachern & Hanson, 2008).

More specifically, this study focuses on a solar hybrid mini-grid installed in the semi-urban community of Bambadinca in Guinea-Bissau. A variation on how the informal grid expanded in relation to the distance from the grid is used. This is in order to isolate the effect of trusting one's neighbour on the development of informal infrastructure from the potential effect of trust on other channels of diffusion (learning, imitation, other types of constraint interactions).

The effect of trust as well as the main determinants of household decisions to connect to the service are being explored through survey elicitation, prior to service commencement, of 396 randomly selected households in the community and through observation of their subsequent decision to connect. The survey also included questions on self-reported trust for neighbours as well as for different actors within the community and questions regarding the household's integration in the community and participation in the project. This was, done to control for other social effects that might be relevant to adoption, in particular drawing from the community driven development literature. After the service commencement, connection patterns were mapped out in detail, to measure each household's distance from the grid and to observe at which point using the neighbour's infrastructure to benefit from lower upfront connection costs, became relevant.

Results indicate that there is some evidence that trusting one's neighbours can affect connections through constraint interactions positively, through inducing the informal expansion of the grid, as the net effect of trusting one's neighbour on connections is positive for households that are farther away from the grid. The decision to connect to the grid was also driven positively by income level, number of adults in the household, ownership status, appliance ownership, prior use of electricity, and negatively by upfront connection costs (as 'proxied' by distance to the grid) and having a female household head. No other trust questions or questions regarding the household's integration in the community were found to be relevant in the general adoption decision.

To my knowledge, this is the first study looking at the underlying social dynamics of constraint interactions, expressed through informal grid expansion. Finally, by looking at the determinants of mini-grid connections I am also informing the electrification and mini-grid literature. To my knowledge this is the first quantitative study looking at the drivers of adoption to community mini-grids and the first study looking at the role of trust on mini-grid adoption.

These findings are important for policy as they show that the social context, appliance possession, income and prior use of electricity should be taken into consideration in the design of electrification projects. Credit schemes and subsidies should also be considered to limit the negative effect of upfront costs on connections and ensure the inclusiveness of groups that are less able to pay.

One of the main limitations of this study like in other studies looking at the role of peer effects in technology adoption is omitted variable bias, in other words the control of unobservables (e.g. unobservable shocks that affect the whole network, or similarities shared amongst households in the same network), that could be driving technology adoption outcomes within groups. Omitted variable bias would be present in this study if an omitted variable correlates with trust for neighbours as well as the connection outcome. Neighbourhoods are compared between them only in comparison to their distance from the grid. However, distance from the grid is not random and a number of household socio-economic characteristics differ according to distance from the grid therefore, the concerns regarding omitted variable bias cannot be eliminated. However, results are robust to controlling for a number of adoption determinants.

This chapter proceeds in the following way: Section 2, presents the case study. Section 3 provides a literature review, Section 4 presents the data collection and Section 5 presents the conceptual framework. Section 6, presents the estimation results and Section 7 concludes with a discussion.

2. Case study

2.1 Country description and ‘Bambadinca Sta Claro’ project

This study took place in the semi-urban community of Bambadinca, which is situated in the Bafatá region in the Northeast part of Guinea-Bissau (See Chapter 1).

The semi-urban community of Bambadinca is the capital of a sector¹⁷ with the same name. According to the latest census Bambadinca has a population of 6,437 inhabitants (RGPH, 2009), this number, has since grown¹⁸ and continues to grow due to a combination of factors which are mostly linked to its geographic location (commerce opportunities, recent infrastructural improvements).

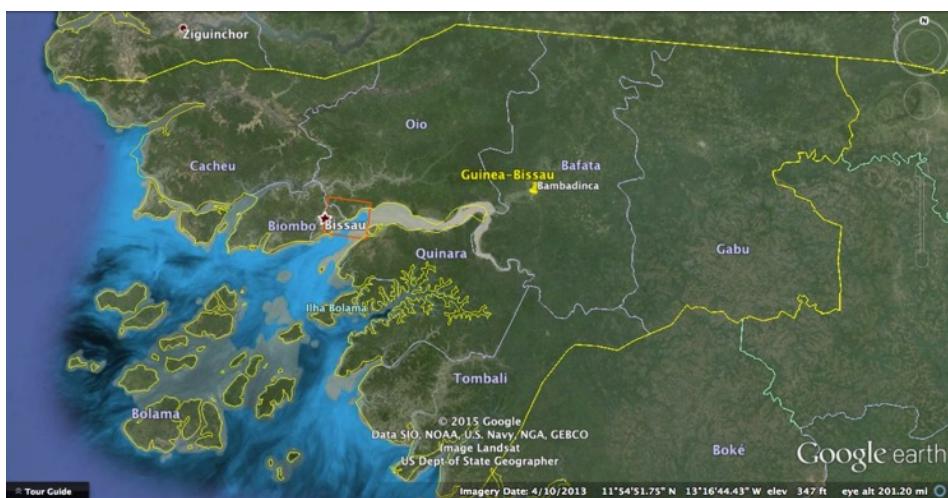
Until 2007 Bambadinca was receiving its energy from a power plant in the city of Bafatá which was operating with diesel generators through a 30KV transmission line. However, after this plant stopped operating and the cables were subsequently stolen, Bambadinca was left literally in the dark. Its population had to rely predominantly on traditional forms of energy (flash lights, candles) and expensive and inefficient alternatives to electrification (including private generators and a private provider called Badora¹⁹) to meet its lighting and cooking needs. This was until November 2014 when a new solar hybrid mini-grid started operating and made electricity available once again to households, businesses and institutions.

¹⁷ The Bafatá region has seven sectors in total

¹⁸ According to a survey conducted by DIVUTEC one of the project’s implementing partners in 2012; the population was estimated to be 8,201 with a total of 780 households (DIVUTEC, 2010).

¹⁹ Badora, serviced Bambadinca (apart from distant areas) only at night through a 115 KVA diesel generator since 2010. In total Badora had 115 clients. Of them only 70 were paying (religious leaders, religious schools and some families were given the service for free). Prices ranged according to installed wattage of equipment, but were overall much higher than what the current mini-grid service is charging (e.g. 1 lamp 40-60 watt would cost 5,000 FCFA per month).

FIGURE 1 MAP OF GUINEA-BISSAU AND BAMBADINCA



This hybrid photovoltaic is the outcome of ‘Bambadinca Sta Claro²⁰ - Programme for Renewable Energy Access’, an innovative project implemented by a Portuguese NGO TESE Development Association(TESE)²¹ and financed by the European Union and the Camões Language and Cooperation Institute as well as United Nations Industrial Development Organisation (UNIDO) and ECOWAS Center for Renewable Energy and Energy Efficiency (ECREE)²². The mini-grid has a 312 kW of installed capacity of 1,248 photovoltaic panels, 216 batteries with a total of 69.000 Ah of storage capacity and three diesel generators of total of 290 kVA back up capacity. It operates under a public community partnership model as Bambadinca’s Development Community Association (ACDB), through the Community Energy Service of Bambadinca (SCEB), manages the service and retains the right to generate, transmit, distribute and sell electricity.

The mini-grid started operating on the 15th of November 2014 with initially 120 clients, through a pilot phase to test the power plant and grid. In this pilot phase the grid was not yet

²⁰ ‘Bambadinca Sta Claro’ in Creole Portuguese means ‘Bambadinca is illuminated’.

²¹ Other project partners include Bambadinca’s Development Community Association (ACDB), the General Directorate of Energy (DGE), the Guinean NGO DIVUTEC and the University of Lisbon. More specifically, ACDB an organization so far responsible for water management in the community was responsible for community mobilization, for project activities and ensuring the provision of the service (through the creation of SCEB which is the energy unit). DIVUTEC was responsible for the information campaign, to organize microcredit activities and a saving scheme in order to help the population meet the upfront connection costs. The University of Lisbon was responsible for sizing of the power plant and LV/MV grid design, training of local technicians and TESE for the execution of the project.

²² The total cost (excluding costs for grid expansion) were 2,140,724 € with 1,605,543€ coming from the ACP European Union Energy Facility and 535,181€ from the Portuguese cooperation (Camoes CICL). UNIDO and ECREE financed the grid extension that was implemented one year after the initial commencement of operations and the technical assistance for operation and management of the grid and the power plant.

fully operational. In that phase clients were charged a flat rate of 3,000 FCFA²³ per month for households and 6,000 FCFA per month for businesses and institutions, regardless of how much electricity they consumed. In April 2015 meters were installed and since then clients are being charged according to how much electricity they consume and at what time of the day they consume this electricity^{24 25}. The payment system is based on prepaid meters that clients have to refill every time they run out of credit and update their meters. By November 2015, 373 clients had connected to the grid including 271 households, 9 institutions and 93 businesses.

The connection costs include the meter rental, which is 15,000 FCFA for households and institutions and 30,000 FCFA for businesses. Clients had to pay another 23,500 FCFA to install the circuit breaker and the electric quadrant, which was mandatory by DGE for security reasons²⁶. Therefore, in total, each household/institution had to pay 38,500 FCFA in addition to the costs to connect to the grid (poles and cables), which varied according to the distance. Every meters of cable costs around 500 FCFA. Poles had to be placed every 35 meters. Small poles cost between 4,500 and 5,500 FCFA and large poles between 5,000 and 6,500 FCFA. For contracts made until 14th of November 2014, 30 meters of free cable were provided to incentivize connections.

A map of the initial main grid can be seen in Figure 2. The main grid was extended in two phases one in the summer of 2015 and one in the spring of 2016. However, for this study only distances from the first phase are relevant as I am focusing on the first stage of connections (connection patterns within the first year until November, 2015). A map with the finalized form of the grid is available in the Appendix.

As far as the informal extension of the grid is concerned some clients came together to share pole and cable costs. In addition, some clients who made the pole and cable investments themselves, sometimes informally charged their neighbours to connect through their infrastructure, and sometimes let them do it for free. The official policy of the service operators was that households who wanted to use their neighbour's infrastructure in order to connect, had to come to an agreement with their neighbours first. In this study this process is what is called the informal extension of the grid. This refers only to the use of the neighbour's connecting infrastructure. As long as the neighbours came to an agreement it was permitted by

²³ The local currency is the Central African Franc (CFA), also represented as XOF or FCFA. The current conversion rate is 633 FCFA to 1 USD.

²⁴ 09h-19h= 250 FCFA per kwh, 19h-24h= 320 FCFA per kwh, 24h-09h = 560 FCFA per kwh.

²⁵ Lower income groups (judged by energy poverty and not income) are charged the first tariff until midnight.

²⁶ Clients could buy these products by themselves.

the service operators. All households had to install a meter and pay for the electricity they consumed regardless of how they connected. No illegal or informal connections were observed. As the service is managed by technicians from the community it is easy to monitor for irregularities.²⁷

FIGURE 2 MAP OF BAMBADINCA AND THE MAIN GRID (BEFORE EXTENSIONS)



²⁷ Some 'spider web' connections were allowed at a later stage of the project, due to a shortage in meters. However, this took place much latter than the time period covered in this study.

2.2 Geography of Bambadinca and community dynamics

All the information in this section was collected during qualitative work conducted prior to the survey, which is discussed in the data and methods section.

Bambadinca consists of three large divisions the ‘Bairros’ (neighbourhoods). As these neighbourhoods have traditionally been distinct entities with different spheres of influence, there has been animosity between them including issues regarding infrastructure sharing. Overall, the community has 5 traditional leaders which consist of decedents of the first families that moved to Bambadinca, and they exert large influence. One of them represents neighbourhood 1, two of them neighbourhood 2 and two more neighbourhood 3.

Apart from the different neighbourhoods there are further 21 smaller subdivisions called ‘zonas’ (zones). These zones were formed either because they had been inhabited by a particular family, ethnic or professional group, or because they used to form separate entities before the expansion of Bambadinca, or due to the timing that they were inhabited. Although the role of the zones used to be more pronounced in the past they still define certain geographic parties within the community. A map with the different neighbourhoods and zones can be found in the Appendix.

Although the leaders were included from the beginning in the consultation processes for the mini-grid project, conflicts have arisen at times. These have been relevant to connection fees, location of infrastructure and the staffing of the service management team. Specifically, leaders from neighbourhood 2 have opposed the project a number of times and have tried to exert their influence on others as well, in order to get concessions from the project providers such as fee reduction. Leaders of neighbourhood 3 and 1, have always been cooperative with project implementers.

Like the rest of the country, Bambadinca is a mix of different ethnicities and religions. The two predominant ethnicities are Fulas and Mandingas who are Muslim, followed by Balantas who are Animists or Christians. Historically within the country there have been tensions between the different ethnicities. More specifically, Balantas tend to be more marginalised. There have also been tensions between the Fulas and Mandingas.

Despite the tensions however, Bambadinca is a community that has been relatively harmonious, and there is a lot of intermarriage between the different ethnicities. Indicative of this, is that one of the reasons that Bambadinca was chosen as the site for the project, was that the community had been successfully managing a communal water supply project through ACDB.

During the set-up of the mini-grid project the implementing partners tried to be inclusive of all ethnicities and neighbourhoods in Bambadinca. However, Mandginas and Fulas dominate both the administration of ACDB and SCEB as well as the two focus groups formed to discuss issues related to the service.

3. Literature review

Overall, the studies looking at electricity adoption in developing countries focus mostly on the socio-economic drivers of connections.

A number of studies have found that electrification in developing countries depends to a varying extent on certain household characteristics, such as household size, income, education, age and gender of household head, employment and appliance possession (Aklin, Bayer, Harish, & Urpelainen, 2015; Kemmler, 2007; Louw, Conradie, Howells, & Dekenah, 2008; Rao & Reddy, 2007; Reddy & Srinivas, 2009), but also on external factors like quality of electricity, tariffs, connection costs, availability of appliances and system reliability (Prasad, 2006 in Louw et al., 2008; Bernard, 2010; Lee et al., 2016).

These studies compare characteristics of electricity users to non-users with the exception of a few experimental studies (Barron & Torero, 2015; Bernard & Torero, 2015; Lee et al., 2016).

Only two studies to my knowledge have looked at the role of peer effects on electricity adoption in developing countries. Barron & Torero, 2015 and Bernard & Torero, 2015 randomly assigned different levels of discount vouchers reducing upfront connection costs and use the variation, to measure the effect of peers on adoption (In El Salvador and Ethiopia respectively). Both studies find a positive effect of discount vouchers on connection decisions and both find evidence of spill-overs (although Barron & Torero, 2015 find these effects to be less strong).

Bernard & Torero, 2015 attribute the effects of these spill-overs on ‘preference interactions’, whereby neighbours try to keep up with connected households as electricity is associated with a social status. Barron & Torero, 2015 attribute these spill-overs to a mix of both learning and imitation effects.

The main limitation of these studies is that, like other studies looking at peer effects on technology adoption, the data does not allow to isolate the exact channels through which peer effects operate. For example, in the Bernard & Torero, 2015 study the hypothesis that peer

effects can be affecting adoption through social learning is rejected, with the claim that the nature of the technology is such that makes it easily observable (Bernard & Torero, 2015). They also present evidence that prior knowledge of electrification and its benefits and how to connect was high. Constraint interactions are also rejected with the claim that there was no evidence of informal connections. Similarly, other technology adoption studies have resorted to result interpretation to understand the way technology diffuses (e.g. Bandiera & Rasul, 2006; Adriazén, 2010).

To my knowledge no study has looked at the underlying social dynamics of constraint interactions, in the case of electrification, even if their importance has been highlighted (Bernard & Torero, 2015; Lee et al., 2016). Barron and Torero, 2015 is the only study looking at the role of informal connections to electrification, albeit focusing on the potentially negative side of informal connections (spider webs) and the implications they might have on the formal connection decisions. The study finds that households with previously informal connections are more likely to undertake a formal connection. The study does not however try to identify the social dynamics that drive these informal connections (Barron & Torero, 2015).

The present study looks at the effect of social capital as measured with trusting one's neighbour on constraint interactions. I exploit a variation caused from distance to the main grid, to isolate the effect of social capital on informal grid expansion from other relevant peer effects. This effect is measured through the interaction of distance from the main grid with social capital measured as trust for neighbours.

Adriazén, 2014 study isolates the role of social capital in social learning for the adoption of cooking stoves in the Peruvian Andes. The study shows that the effect of social capital on cookstove usage is present only in communities that have a positive experience with the cookstove, the study demonstrates that social learning is the dimension of social capital influencing adoption decisions. Two measures of social capital are elicited, which are aggregated at the village level. One is trust for neighbours measuring internal social capital at the community level (bonding capital), and the other is trust for strangers measuring external ties with other communities (bridging capital). It is demonstrated that only bonding social capital affects adoption decisions through its interaction with successful adoption by others (Adriazén, 2014).

This study similarly tests if trust for neighbours only has a positive effect on connection decisions for households that are farther away from the grid, which would be an indication that trust for neighbours enhances collaboration between neighbours to bring about the informal expansion of the grid.

The choice of reference group is also important in the study of peer effects. Some studies resort to specific reference groups at the neighbourhood, school or community levels and others to self-reporting (e.g. Conley & Udry, 2010). Kremer & Miguel, 2007 find this choice to have significant implications on their findings. In the present study, as by definition infrastructure sharing is relevant within neighbourhoods, the level of the social group is by definition the neighbourhood.

Finally, this study contributes to literature on mini-grids. To my knowledge no study up until now has tried to measure quantitatively what drives connections to mini-grids and the underlying economic, social and spatial dynamics. The existing literature on mini-grids consists of descriptive case studies (Chakrabarti & Chakrabarti, 2002; Kivaisi, 2000) and analysis of the technical performance and cost effectiveness, in comparison with other isolated off-grid solutions (Chaurey & Kandpal, 2010; Jiayi, Chuanwen, & Rong, 2008; Moharil & Kulkarni, 2009). In addition, a number of largely descriptive studies have looked on the financial sustainability of mini-grids, focusing on the ability of mini-grids to cover operating costs, the role of local authorities and local populations, maintenance procedures, and availability of spare parts (Kirubi, Jacobson, Kammen, & Mills, 2009; Nouni, Mullick, & Kandpal, 2006). Finally, a number of studies have looked at the socio-economic effects of mini-grids (Chakrabarti & Chakrabarti, 2002; Kirubi et al., 2009). (Ulsrud, Winther, Palit, Rohracher, & Sandgren, 2011 provide a discussion).

The importance of community participation for the success of rural electrification has been underscored in a number of studies (see Schillebeeckx, Parikh, Bansal, & George, 2012; Hirmer & Cruickshank, 2014) as has the role of social dynamics on the success of mini-grid projects (Rolland & Glania, 2011). However, it “hasn’t yet been empirically studied if local participation leads to better suited and hence more efficient and more sustainable designs or to elite capture and lower performance” (Bernard, 2010).

Community based and community driven projects are thought to have a certain number of advantages as they allow for better use of local knowledge, encourage the building of social capital, render the benefits of the projects more inclusive and empower the more marginalized strands of the society. However, empirical evidence is mixed, suggesting that these projects can create effective infrastructure, but are not necessarily effective in reaching the poor, as benefits are often captured by powerful elites (See Mansuri & Rao, 2004 for a review). This elite domination, is more pronounced in unequal and more heterogeneous societies (on “factional, ethnic, or religious identity”) where leaders are not accountable (in Mansuri & Rao, 2004).

This study also looks at how these highlighted concerns might apply in the case of a community mini-grid, by looking at how participation in the project, marginalisation, embeddedness in the community, divisions within the community and the role of leaders in aggravating these divisions can affect the decision to connect. However, these effects are only measured with survey indicators (e.g. trust for different actors, collective action, participation in the project).

4. Data and methods

The main determinants of household decisions to connect to the service are being explored through survey elicitation, prior to service commencement, of 396 randomly selected households in the community and through observation of their subsequent decision to connect after the service operation started.

A baseline survey was undertaken to gather information on current energy consumption, income and other socio-economic information three months prior to the service commencement. The survey took place between 16/6/2014- 23/7/2014 with three enumerators. Each survey lasted around 1 hour. The survey was conducted in the local Portuguese Creole language. 396 households were surveyed with no businesses included. A random probabilistic sample at the household level of the community was selected, based on information on inhabitants collected prior to the survey.

As it was not possible to acquire lists of inhabitants from the census, a list of the inhabitants was created using google maps. I took samples from the whole targeted population, and randomized from smaller subdivisions (stratified sampling at the neighbourhood level) in order to make sure that there would be a balanced geographic representation. The person who was responsible for energy purchase decisions was interviewed, or if that person was not there a person that was knowledgeable about the household's affairs was interviewed instead. If no one was available, the enumerators were instructed to return later or move to the next household on the list. Overall, only 3 households refused to participate in the survey, and the enumerators were not able to reach 9.5% of the initial draw²⁸.

Prior to the survey a number of interviews with project implementers and two focus groups, one with community leaders and one with inhabitants, helped formulate and test the

²⁸ I assume MCAR (missing completely at random): non response probability the same for everyone.

questionnaire so as to understand better intra-household and community dynamics and energy use patterns.

The survey included standard demographic questions and questions about energy use patterns. In addition, as the majority of households do not receive a stable income, a number of questions regarding the quality of the dwelling as well as the household's possessions, were included to construct an income indicator. This is explained in more detail in the Appendix.

Apart from self-reported trust for one's neighbours a number of other trust, and questions regarding the household's integration in the community and participation in the project were also elicited. This was done to test the general effects of trust on project success and the potential effects of divisions within the community on the decision to connect.

Following a widely practiced method (e.g. General Social Survey, World Bank Social Capital Initiative²⁹), households were asked to state their level of agreement with statements, expressing their level of trust regarding different actors in Bambadinca in a five-point scale (the community, friends, neighbours, relatives, people of other ethnicities, people of other neighbourhoods). They were also asked to state their level of trust for formal and informal institutions (traditional leaders, NGOs, local government) and generally state their feeling of belonging in the community. These were thought to encompass all potential expression of social capital influencing project success, and to express all potential divisions within the community³⁰. To be able to fully explore the role of potential differences between groups within the community, questions about the household's ethnicity, religion and years residing in Bambadinca were also elicited.

In addition, questions were asked about membership to community organisations, work done for the community and one's ability to borrow money in time of need. Finally, questions regarding familiarity with the service and level of household participation in the service, were included, to check whether knowledge and participation affect service adoption. A complete draft of the survey can be found in the Appendix.

Interviewed households were marked in a map in order to observe their decision to adopt to the service and to study the spatial dynamics (distance from the grid, neighbourhood). All clients using the service were also marked in a map, in order to be able to match them with

²⁹ The Social Capital Initiative refers to an effort by the World Bank to provide a better definition and measurement for concept for social capital in the context of development (see (Krishna & Shrader, 2000) for an example of questionnaire design).

surveyed households. The process of informal grid expansion was also mapped. ‘GoogleEarth’ was used for the initial mapping and ArcGIS for the measurement of distances.

Only the connection patterns of the first year were studied (clients that had connected until November, 2015). The main reason for this is to ensure that surveyed households are properly matched with the service clients. This has been done for all clients until November 2015. In addition, it is assumed that with the passage of time there is a higher likelihood that surveyed households could start moving around or outside the community.

5. Estimated model of binary logistic regression

The impact of the household characteristics on the dichotomous decision to connect or not to the mini-grid, is initially analysed through a binary logistic regression model, which is commonly used in technology adoption studies (Bhandari & Jana, 2010; Walekhwa, Mugisha, & Drake, 2009). Probit and linear probability models were subsequently also tested to ensure the robustness of results.

The logistic regression model is used when the dependent variable describes a binary discrete outcome. The logistic model is estimated using the maximum likelihood estimation. The dependent variable is transformed into a logit variable, which estimates the natural log odds (odds are the ratio of the probabilities of the event and the non-event) of the occurrence of a particular event.

More specifically, the binary logistic model is specified for the logit transformed odds of $Y_i = 1$ as follows:

$$Y_i = \ln \left(\frac{\pi_i}{1 - \pi_i} \right) = a + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}$$

$$\pi_i = \frac{e^{a + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}}}{1 + e^{a + \beta_1 X_{1i} + \cdots + \beta_k X_{ki}}} = \frac{1}{1 + e^{-(a + \beta_1 X_{1i} + \cdots + \beta_k X_{ki})}}$$

Where Y is a binary response variable with values 0 and 1 and observations Y_i are statistically independent of each other. The log of the odds ratio (called the logit) is a linear function of the k explanatory variables $X_1 + \dots + X_k$. $P(Y_i = 1 = \pi_i)$ is the probability ranging between 0 and 1 and it is a non-linear function of the independent variables. $\beta_1 + \dots + \beta_k$ are the parameter of the model, which are interpreted as partial (log) odd ratios. This holds for n observations $i = 1, \dots, n$.

Alternatively, instead of interpreting the coefficients on the log-odds scale one can take the exponential and interpret coefficients directly as odds ratios.

The odds ratio is expressed as:

$$\frac{\pi_i}{1 - \pi_i} = \frac{1 + e^{(a + \beta_1 X_{1i} + \dots + \beta_k X_{ki})}}{1 + e^{(a + \beta_1 X_{1i} + \dots + \beta_k X_{ki})}} = e^{(a + \beta_1 X_{1i} + \dots + \beta_k X_{ki})}$$

For the present study this model can be described as π_i being the probability of connecting to the grid (judged by observed connections of surveyed households) and $X_1 + \dots + X_k$ the independent variables influencing the probability of connecting to the mini-grids. $\beta_1 + \dots + \beta_k$ are the estimated coefficients.

Two relationships with distance to the main grid are explored. A threshold effect and an effect which increases with distance. For the threshold effect, a binary distinction is made between households that are close to the grid and do not benefit from the informal grid expansion, and households that are farther away from the grid and therefore the informal expansion of the grid could potentially reduce their connection costs. From observed connection patterns it was established that no infrastructure sharing took place below a 30-meter distance from the main grid (a map with connection patterns is available in the Appendix).

Therefore, a 30-meter distance from the grid was established as the threshold effect. Being at least 30 meter away from the grid is interacted with trust for neighbours to measure the possible separate effect of social capital. The second relationship assumes that the effect of social capital on informal grid expansion increases with distance from the main grid. Therefore, the log distance from the main grid is interacted with trust for neighbours.

6. Descriptive statistics

6.1 Household characteristics

Tables 1 and 2 list the summary statistics of the sample as far as the main household characteristics are concerned. 396 households were interviewed. Around 58% of respondents were the head of the family and 74% reported to be direct decision makers regarding the choice on energy purchase. 54% of respondents were male with the average age being 40.5. The average household size was found to be 11.3. In addition, 19% of households reported to have a female head³¹ and 28% of households reported that they receive remittances from abroad.

Overall, the sample consists of households that have lived in Bambadinca for a long time. The majority of these households also own the houses they live in (78%). The grand majority has children, and these children are going to school, although education levels are low.

As far as employment is concerned the most common occupation is some form of commerce or agricultural activity and only 30% of households have a member that receives a fixed salary. Households overall report to save very little and experience at least some hardship during the rainy season (seasonality of income).

Regarding geographic representation 11% of surveys took place in neighbourhood 1, 62 in neighbourhood 2 and 26% in neighbourhood 3. In an internal survey that took place in 2011 from one of the implementing partners the percentage of the population was found to be 11% in neighbourhood 1 64% in neighbourhood 2 and 24% in neighbourhood 3 (DIVUTEC, 2010). Therefore, each neighbourhood was well represented in the survey.

³¹ These numbers demonstrate that in Bambadinca women have a significantly higher participation in decision making in the household than in the other communities in Bafatá surveyed in Chapter 1.

TABLE 1 DESCRIPTIVE STATISTICS OF HOUSEHOLD CHARACTERISTICS

Sample size	396	Households who have a female head	18.94%
Household connected by November 2015	28.25%	Households who receive remittances from abroad	27.78%
Respondent is decision maker about energy	73.74%	Households with children	95.45%
Respondent is male	54.04%	Average number of children	4.69
Respondent is head of the family	57.83%	Households whose children go to school	86.11%
Average age of respondent	40.51	Households who receive a fixed salary ³²	30.71%
Average household size	11.3	Households who reside in Bambadinca for more than 40 years	48.23 %
Household owns house	78.03%	Households who reside in Bambadinca for more than 5 and up to 40 years	33.59%
		Households who moved to Bambadinca in the last 5 years	13.13%

TABLE 2 DESCRIPTIVE STATISTICS OF HOUSEHOLD CHARACTERISTICS (CONTINUED)

Respondent's schooling		Ethnicity	
Never went to school	39.49%	Fula	46.97%
Primary education	32.66%	Mandinga	17.68%
Secondary education	24.56%	Balanta	17.42%
Higher education	3.29%	Beafada	4.29%
Higher schooling in the family		Papel	2.02%
Never went to school	4.29%	Other	11.61%
Primary education	29.8%	Household employment	
Secondary education	60.10%	Public employee	19.44%
Superior education	5.81%	Private employee	16.16%
Neighbourhood 1	11.62%	Commerce & Services	40.66%
Neighbourhood 2	62.12%	Agriculture	70.2%
Neighbourhood 3	26.26%	Fisheries	3.03%
		Small commerce	60.86%
		Animals	4.55%
		Other	6.82%

³² The survey took place at a time when the majority of civil servants were not receiving their salaries due to political problems. For this reason, respondents were asked to state if there was someone in the household who normally received a fixed salary.

6.2 Energy use

The majority of the households in Bambadinca used traditional forms of lighting (candles, flashlights and battery powered lamps) prior to the commencement of the service (Table 3). Electricity (Badora, frequently used generators, solar panels) was used by a very small fraction of the population. It should be clarified that although a substantial proportion of the population possessed generators (25%) they tended to use them infrequently and not in order to meet their daily energy needs.

However, a larger fraction of the population possessed energy durables. The most common being TVs, DVDs and lamps, followed by fans, TV antennas, fridges, computers and irons. This can be attributed to the fact that 26.5% of the population was previously connected to the public grid. The large percentage of households possessing radios (85%), and mobile phones (98%), can be attributed to the fact that they had alternative means to power them (batteries, charge in stores).

TABLE 3 HOUSEHOLD ENERGY USE PATTERNS

Lighting		Possession of energy durables	
Household uses candles	40.66%	Lamps	30.05 %
Household uses flashlight	92.17%	TV	34.60 %
Household uses battery powered lamp	72.22 %	Fan	14.39 %
Household uses other equipment with batteries (for lighting)	2.02 %	Fridge	8.08 %
Household uses solar panels	1.26%	Computer	6.57 %
Household uses car batteries	0.75%	Iron	6.57 %
Household possess generator	24.75%	Satellite dish	9.09 %
Household uses generator frequently	4.8%	DVD	30.3%
Household was client of Badora	8.33%	Radio	85.61%
Household was connected to the public grid	26.58%	Mobile phone	98.23%
		Other	2.53 %

6.3 Self-reported trust

Overall the level of trust in Bambadinca is high (Table 4). Households demonstrate very high levels of trust for the majority of the community in general as well as their families. These numbers are slightly lower for traditional leaders, friends, and neighbours, and much lower for people of other ethnicities and other neighbourhoods. As far as more formal actors and institutions external to the community are concerned, trust for NGO's in general and the mini-grid project in particular is high. Trust for the local government is lower although still relatively high.

Responses to trust questions are assumed to be the proxy of social capital for the household level, as we were not always able to interview the decision maker.

More descriptive statistics regarding households' participation in the project, knowledge of the project as well as membership in organisations and participation in collective action for the community are presented in the Appendix.

TABLE 4 SELF-REPORTED TRUST QUESTIONS

	Trust a lot	Trust	Neither trust nor distrust	Distrust	Distrust a lot
People in the community	32.58%	60.10%	4.04%	2.02%	1.26%
Family	71.72%	24.24%	0.76%	2.53%	0.76%
Friends	32.32 %	52.02 %	8.84 %	6.06 %	0.76 %
Neighbours	23.04 %	54.18 %	9.87 %	12.15 %	0.76 %
Traditional leaders	46.21%	41.92%	7.32%	3.03%	1.52%
Other neighbourhoods	8.33%	40.15%	25.00%	23.74%	2.78%
Other ethnicities	14.68%	47.09%	18.48%	18.48%	1.27%
Implementers of the mini-grid project	55.70%	34.68%	7.09%	2.53%	
The local government	19.70%	52.02%	15.66%	12.12%	0.51%
NGOs	35.44%	48.35%	9.62%	6.33%	0.25%

6.4 Statistics of distance from the grid

Table 5 reports the summary statistics of the distance from the main grid of all surveyed households, and also separately for the surveyed households that ended up connecting to the service. Around 30% of surveyed households are below a 30-meter distance from the main grid and 75% of surveyed households are up to roughly 120 meter away from the main grid. The maximum distance from the main grid of a connected household is 415 meters, however the majority who connected was 70 meters away from the grid or closer.

Table 6 provides an estimation of how distance to the grid translates to connection costs based on the cost information presented in Section 2. As pole costs can vary the average cost of each pole is assumed to be 5,000 FCFA for this estimation. It becomes clear that these variable costs constitute a large part of the connection costs. The variable costs become the largest part of the connection costs for households that are 70 meters away from the grid. As distances increase even more these variable costs become very high.

TABLE 5 SUMMARY STATISTICS OF DISTANCE FROM THE GRID FOR SURVEYED HOUSEHOLDS

Surveyed households	Distance from the main grid in meters	Surveyed households who connected	Distance from the main grid in meters
25%	24.24	25%	19.39
50%	64.85	50%	39.16
75%	121.24	75%	71.78
99%	596.64	99%	253.15
Largest	634.39	Largest	414.53
Mean	88.79	Mean	57.95
Surveyed households located below 30 meters from the main grid	30.25%		

TABLE 6 ESTIMATED CONNECTION COSTS ACCORDING TO DISTANCE FROM THE GRID

Distance from the grid (in meters)	Estimated variable costs of connection (FCFA)	Total costs of connection: Including fixed costs and variable costs (FCFA)
0	0	38,500
35	22,500	61,000
70	45,000	83,500
105	67,500	106,000
140	90,000	128,500
175	112,500	151,000
210	135,000	173,500
245	157,500	196,000
280	180,000	218,500

Variable costs: Assuming one pole is needed for each 35 meters, 500 FCFA per meter of cable, 5000 FCFA per pole.

7. Results

7.1 Effects of trust for neighbours on the informal expansion of the grid

Table 7, 8 and 9 show the effect of trusting one's neighbour on the informal expansion of the grid.

For the logistic regression model, as well as the probit and OLS models trusting one's neighbour has no effect on the overall connection decisions at the community level (column 1). However, interactions with distance from the grid show a significant additional positive effect of trust levels for one's neighbour on connection decisions for households that are 30 meters away from the grid (column 3). This is attributed to the effect of trusting one's neighbour on informal grid expansion. The overall effect of trusting ones' neighbour for households that are 30 meters away from the grid is also positive and significant. It is also possible that the negative baseline is driven by the presence of other peer effects that have a negative effect on connections (e.g. ability to use the electricity of a connected neighbour). However, the baseline is not significant in the OLS model.

The effect of trusting one's neighbour interacted with the log distance from the grid, is also significant with the same signs. However, it loses significance for the OLS model. This demonstrates that it is less clear if the effect of co-operation for informal grid expansion increases the farther away one moves from the grid. One explanations behind this is that as most connections occur within a certain distance from the grid the informal expansion of the grid might be less relevant for households located very far.

TABLE 7 LOGISTIC REGRESSION MODEL ON CONNECTION DETERMINANTS WITH TRUST FOR NEIGHBOURS
INTERACTED WITH DISTANCE FROM THE MAIN GRID

	(1)	(2)	(3)			
	Coefficient (std. err)	Marginal effect (std. err)	Coefficient (std. err)	Marginal effects (std. err)	Coefficient (std. err)	Marginal effects (std. err)
Log distance	-0.426* (0.231)	-0.057* (0.032)	-0.886*** (0.336)	-0.110** (0.046)	-1.429** (0.645)	-0.190** (0.08)
Trust neighbours	0.026 (0.210)	0.003 (0.028)	-0.944** (0.437)	-0.117*** (0.044)	-0.995* (0.597)	-0.132* (0.07)
Trust neighbours *30meters			1.287** (0.553)	0.160*** (0.052)		
30 meters			-4.032** (2.031)	-0.695** (0.274)		
Trust neighbours *Log distance					0.250* (0.145)	0.033* (0.018)
<i>Log likelihood</i>	<i>-122.71</i>		<i>-117.87</i>		<i>-122.04</i>	
<i>N</i>	383		383		383	
<i>Pseudo R2</i>	0.46		0.48		0.46	

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All regressions in this table control for all variables included in the regression in table 10. In all regressions, the standard errors are clustered at the zone (smaller divisions of the neighbourhoods) level.

TABLE 8 PROBIT REGRESSION MODEL ON CONNECTION DETERMINANTS WITH TRUST FOR NEIGHBOURS INTERACTED WITH DISTANCE FROM THE MAIN GRID

	(1)	(2)		(3)		
	Coefficient (std. err)	Marginal effects (std. err)	Coefficie nt (std. err)	Marginal effects (std. err)	Coefficient (std. err)	Marginal effects (std. err)
Log distance	-0.255** (0.129)	-0.064** (0.032)	-0.513*** 0.187	-0.122*** (0.04)	-0.772** (0.337)	-0.193** (0.080)
Trust neighbours	-0.0008 (0.106)	-0.0002 (0.026)	-0.487** (0.211)	-0.116*** (0.043)	-0.526* (0.297)	-0.131* (0.070)
Trust neighbours *30meters			0.647** (0.271)	0.154*** (0.055)		
30 meters			-1.977** (0.971)	-0.59** (0.266)		
Trust neighbours *Log distance					0.129* (0.075)	0.032* (0.018)
Log likelihood	-121.95		-117.72		-120.01	
N	383		383		383	
Pseudo R2	0.46		0.48		0.47	

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All regressions in this table control for all variables included in the regression in table 10. In all regressions, the standard errors are clustered at the zone (smaller divisions of the neighbourhoods) level.

TABLE 9 OLS REGRESSION MODEL ON CONNECTION DETERMINANTS WITH TRUST FOR NEIGHBOURS INTERACTED WITH DISTANCE FROM THE MAIN GRID

	(1)	(2)	(3)
	Coefficient (std. err)	Coefficient (std. err)	Coefficient (std. err)
Log distance	-0.044* (0.024)	-0.065** (0.030)	-0.102** (0.043)
Trust neighbours	0.012 (0.020)	-0.057 (0.034)	-0.048 (0.051)
Trust neighbours *30meters		0.098* (0.046)	
30 meters		-0.335* (0.163)	
Trust neighbours *Log distance			0.014 (0.012)
N	383	383	383
R2	0.45	0.47	0.46

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All regressions in this table control for all variables included in the regression in table 10. In all regressions, the standard errors are clustered at the zone level (smaller divisions of the neighbourhoods) level.

7.2 Other connection determinants

Table 10 reports the determinants of connecting to the grid. A table with an explanation of all variable names used in the regressions can be found in the Appendix. Most of the determinants that were found to have no significant effect are not presented in the table, but are included as controls in the regressions. All the included controls were checked for multicollinearity.

Most of the results in the models are expected by theory. Holding all else constant distance from the grid has a significantly negative effect on households' connections. The main reason behind this is that distance from the grid increases the variable costs of connection since more cable and poles are required. The negative effect of the size of upfront connection costs on electrification has been shown in a number of other studies (e.g. Bernard & Torero, 2015; Lee et al., 2016).

Income indicators were included as dummies, with setting the poorest bracket as the baseline. Expectations from theory were confirmed. Lower medium, higher medium and richer income brackets, in comparison to the poor income bracket have a positive significant effect on connecting, which increases with the income category. The number of adults in the household also has a significant positive effect on connection.

Having a head of the household who is female also has a significant negative effect on connection. One explanation behind this is that overall the income levels of female headed households are lower, but this is not the case in our sample therefore it is harder to interpret this finding.

Equipment possession prior to connection not only reveals higher socio-economic status for the household and a prior experience with electricity, but also lowers costs associated with connections and entails higher benefits associated from the use of electricity. As expected possessing a TV and a fridge have a positive significant effect on connecting.

In addition, as expected previous use of electricity and specifically being a Badora customer prior to the connection have a positive effect on connecting to the new service, as is to be expected.

Being an owner of the house the family resides in, has a large positive significant effect. This is expected as non-ownership of one's house renders the investment of electricity more uncertain (Barron & Torero, 2015).

Participation in an activity related to the administration or technical implementation of the project has a positive significant effect. But participation in activities related to the

construction process has no effect³³. No trust variables or other variables capturing the respondent's integration in the community (collective action, ability to borrow money in times of need, membership in community organisations and residing in Bambadinca for less than 5 years) did not appear to have any effect on connecting to the service. And neither does household ethnicity or the neighbourhood one is located in.

Household employment in commerce has a negative effect on connections. This result runs contrary to my priors, as households who were involved in commerce are expected to be better off and have a higher demand for connections. A possible explanation is that households who ran a commerce are more likely to have electricity for their business, which they could use to connect their households and avoid additional connection costs.

Overall, the results are largely in line with other findings in the literature of electrification underscoring the importance of previous experience with electricity, income levels and possession of appliances as main determinants for connections (e.g. Barron & Torero, 2015).

³³ 33% of surveyed households had a member who actively participated in the project the majority of which participated in construction (28%) and much fewer (5%) participated in an activity related to the administration or technical implementation of the project.

TABLE 10 CONNECTION DETERMINANTS

	Logistic model		Probit model		OLS model
	Co-efficient (std. err)	Marginal effects (std. err)	Co-efficient (std. err)	Marginal effects (std. err)	Co-efficient (std. err)
Log distance	-0.426* (0.231)	-0.057* (0.032)	-0.255** (0.129)	-0.064** (0.032)	-0.044* (0.024)
Number of adults	0.068** (0.034)	0.009* (0.004)	0.040** (0.019)	0.010** (0.005)	0.008* (0.004)
Female head	-0.807** (0.351)	-0.091* (0.036)	-0.410** (0.179)	-0.090** (0.036)	-0.075 (0.048)
Private business	-0.884** (0.362)	-0.111** (0.043)	-0.534*** (0.203)	-0.126*** (0.047)	-0.069*** (0.040)
Fridge	1.147* (0.597)	0.204 (0.141)	0.687** (0.320)	0.215* (0.124)	0.181** (0.075)
TV	1.229*** (0.402)	0.187** (0.075)	0.671*** (0.214)	0.184*** (0.067)	0.202*** (0.048)
Generator	1.202 (0.873)	0.221 (0.198)	0.752 (0.496)	0.243 (0.188)	0.170 (0.143)
Badora	2.109* (1.100)	0.429* (0.265)	1.158** (0.524)	0.394* (0.206)	0.254* (0.124)
Lower medium income level	1.271*** (0.395)	0.205*** (0.077)	0.681*** (0.192)	0.194*** (0.063)	0.116** (0.043)
Upper medium income level	1.293** (0.549)	0.217** (0.112)	0.744*** (0.266)	0.221** (0.091)	0.126** (0.052)
Richest income level	2.441*** (0.491)	0.454*** (0.102)	1.363*** (0.238)	0.432*** (0.083)	0.269*** (0.061)
Owner of house	2.753*** (0.458)	0.234*** (0.039)	1.566*** (0.229)	0.252*** (0.036)	0.192*** (0.041)
Neighbourhood 2	-1.223 (0.832)	-0.181 (0.140)	-0.700 (0.442)	-0.189 (0.130)	-0.103 (0.105)
Participation	1.716** (0.777)	0.344* (0.186)	1.028** (0.435)	0.351** (0.168)	0.246** (0.109)
Constant	-3.085** (1.226)		-1.619** (0.645)		0.123 (0.153)
<i>Log likelihood</i>	<i>-122.71</i>		<i>-121.95</i>		
<i>N</i>	383		383		383
<i>Pseudo R2 /R-squared</i>	0.46		0.46		0.4586

*p-value<0.1 **p-value<0.05 ***p-value<0.01. In all regressions, the standard errors are clustered at the zone (smaller divisions of the neighbourhoods) level. The regression controls additionally for other variables regarding socio-economic characteristics of the household and the respondent (number of children, level of education, ethnicity, receiving remittances from abroad, receiving a fixed salary, being employed only in agriculture), energy usage patterns (being connected in the past to the public electricity service, owning a fan, owning a computer, owning an iron), self-reported trust (for other ethnicities, government officials, NGOs, neighbours, friends) and other variables regarding the household's integration in the community and participation in the project (frequency with which respondent undertakes collective action in the community, ability to borrow money in time of need, household membership in community organizations, living in Bambadinca for less than 5 years, household participation in the construction of the project).

7.3 Limitations

One of the main limitations of studies measuring peer effects on technology adoption is omitted variable bias, in other words, not controlling for unobservables. These could be either common shocks, that are experienced equally by the whole social group and also affecting technology adoption decisions, or common characteristics shared by a social group, that also affect technology adoption decisions (see Adrianzén, 2014 for a discussion).

In this study it is possible that an omitted variable correlates both with the level of trust for neighbours and the connection decision.

The main grid was not designed at random but follows closely to patterns of the previous public grid or the grid used from Badura, therefore it tends to pass closer from the centre of commercial activity. Households who are better off tend to be closer to the grid. However, the grid also passes from other less vibrant parts of the community. The findings could therefore be biased if households closer to the grid differ from those farther from the grid in certain characteristics that correlate with trust between neighbours and connection decisions. These limitations cannot be fully addressed. However, results are robust to controlling for a number of adoption determinants. In addition, Table 11 reports no indication that levels of trust for one's neighbours change according to the distance from the grid.

Finally, another potential bias would arise if higher connection density affected peer effects, as connections are higher the closer one is to the main grid due to lower upfront connection costs and higher income levels. If that were the case the effect of trust for neighbours in the informal expansion of the grid can not be fully isolated, from other potential channels by which it could be affecting the connection decision, with using distance from the grid as a criterion. However, as the study is within the community level, overall distances between households are small and therefore it is unlikely that differences in connection density would affect peer effects drastically.

TABLE 11 RELATIONSHIP OF TRUST AND DISTANCE FROM THE GRID

Below 30 meters from the grid	Above 30 meters from the grid	P-value
Trust neighbours (5- point scale 1=distrust a lot 5= trust a lot)	3.892	3.854

The table validates that the two groups in the survey are balanced across self-reported trust for neighbours. The p-value is derived from a t-test.

8. Conclusions

This study looks at the effect of social capital as measured in trust for one's neighbours in connections to a solar hybrid mini-grid that started operating in the fall of 2014 in the semi-urban community of Bambadinca in Guinea-Bissau. A variation on informal grid expansion due to distance from the main grid is used in order to isolate the effect of social capital as expressed with trust in neighbours on informal grid expansion from other potential peer effects. The level of trust amongst neighbours is expected to affect the successful informal expansion of the grid as neighbours need to come to an agreement on how to share the costs or to allow each other to use their infrastructure. In addition, the main determinants of household decisions to connect to the service are explored through survey elicitation prior to service commencement of the 396 randomly selected households in the community, and through observation of their subsequent decision to connect.

Results demonstrate that for households that are at least 30 meters away from the grid, trusting their neighbour has an additional positive effect on connecting, as opposed to households living less than 30 meters away from the grid. However, the total effect of trust for this group is small.

Results demonstrate that the decision to connect to the mini-grid is driven positively by income level, house ownership, appliance ownership (TV, fridge), the number of adults in the household and previous electricity use patterns, and negatively by having a female household head and upfront connection costs (as 'proxied' by the distance to the grid). The majority of these findings have been confirmed in a number of studies (Aklin et al., 2015; Gaunt, 2005; Kemmler, 2007; Louw et al., 2008; Barron & Torero, 2015; Bernard, 2010; Bernard & Torero, 2015; Lee et al., 2016; Rao & Reddy, 2007; Reddy & Srinivas, 2009).

As far as variables capturing the household's integration in the community and participation in the project, only participation in an activity related to the administration or technical implementation of the project has a positive significant effect. However, this type of participation concerns only a small share of the population. No other trust or other social capital question (collective action, ability to borrow money in times of need, membership in community organisations, year residing in Bambadinca) appeared to have any effect. These findings indicate that embeddedness in the community and level of marginalisation do not play a role in the connection decision.

However, although community divisions do not seem to play a negative role on connections to the service, some groups are still benefiting less from the service judging from the low connection rates of female headed households and of lower income households.

To my knowledge this is the first study which looks at the drivers of adoption to community mini-grids, and the first study which researches social capital effects on mini-grid adoption. In addition, it is one of the few studies that looks at the effect of social capital on electrification. The novelty of the study lies in the fact that the different channels of social capital are captured not only through using a variety of trust questions, but also through exploiting a variation of distance from the grid and therefore isolating the effect of social capital on informal grid expansion. To my knowledge it is also the first work which studies the potential positive effect of informal grid expansion on electrification and its underlying social dynamics. So far informal grid expansion has been widely ignored and these type of constraint interactions have been only studied in the form of informal connections and their potential barrier to formal connections (Barron & Torero, 2015). It is important to acquire a broader understanding of such a prevalent phenomenon in developing countries that can significantly reduce technology adoption costs.

There are some limitations in this study. I am assuming that there are no unobservable characteristics, that differ between households that are closer and farther away from the grid, and correlate with trust for one's neighbours and the decision to connect. The concerns regarding omitted variable bias cannot be eliminated. However, results are robust to controlling for a number of adoption determinants.

Finally, I assume that other peer effects are similar across Bambadinca, which could not hold if for example connection density influences the magnitude of peer effects.

As far as the other findings are concerned, this study does not control for all the possible mediating effects. For example, discounting, risk preferences and liquidity constraints were not taken into consideration, and they could be mediating income effects.

These findings are important for policy as they shed more light on the underlying dynamics of electricity adoption decisions. As a number of electrification projects suffer from low adoption rates it is crucial that we are able to understand the drivers of connection decisions. This study shows that electrification projects are more likely to achieve higher connection rates in environments where households have higher income means and already use some form of electricity and possess appliances. The provision of credit and subsidies to reduce the burden of connection costs should be considered as well. Attention should be placed not only in alleviating the 'fixed costs' of connection but also on the 'variable costs', which can

constitute an even bigger impediment. The provision of subsidies should also be considered in order to reach the poorest strands of the society.

This study demonstrates some evidence that trust for one's neighbours can indeed increase connections through the informal expansion of the grid. Therefore, the social context can play a role for the success of electrification projects.

More research however is necessary to understand the other channels by which social capital can operate on the connection decisions and how they can potentially cancel each other before making more conclusive recommendation about the benefits of certain social contexts. The need to isolate properly peer effects on electrification, as they could be neutralizing each other, has also been underlined from other authors (Lee et al., 2016).

9. References

Adrianzén, M. A. (2014). Social capital and improved stoves usage decisions in the northern Peruvian Andes. *World Development*, 54, 1-17.

Aklin, M., Bayer, P., Harish, S., & Urpelainen, J. (2015). Quantifying slum electrification in India and explaining local variation. *Energy*, 80, 203-212.

Bandiera, O., & Rasul, I. (2006). Social networks and technology adoption in northern Mozambique. *The Economic Journal*, 116(514), 869-902.

Barron, M., & Torero, M. (2015). Fixed Costs, Spillovers, and Adoption of Electric Connections.

Bartholomew, D. J., Steele, F., Galbraith, J., & Moustaki, I. (2008). *Analysis of multivariate social science data*: CRC press.

Bernard, T. (2010). Impact analysis of rural electrification projects in sub-Saharan Africa. *The World Bank Research Observer*, lkq008.

Bernard, T., & Torero, M. (2015). Social interaction effects and connection to electricity: Experimental evidence from Rural Ethiopia. *Economic development and cultural change*, 63(3), 459-484.

Bhandari, A. K., & Jana, C. (2010). A comparative evaluation of household preferences for solar photovoltaic standalone and mini-grid system: An empirical study in a costal village of Indian Sundarban. *Renewable Energy*, 35(12), 2835-2838.

Booyse, F., Van Der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2008). Using an asset index to assess trends in poverty in seven Sub-Saharan African countries. *World Development*, 36(6), 1113-1130.

Chakrabarti, S., & Chakrabarti, S. (2002). Rural electrification programme with solar energy in remote region—a case study in an island. *Energy Policy*, 30(1), 33-42.

Chaurey, A., & Kandpal, T. (2010). A techno-economic comparison of rural electrification based on solar home systems and PV microgrids. *Energy Policy*, 38(6), 3118-3129.

Conley, T. G., & Udry, C. R. (2010). Learning about a new technology: Pineapple in Ghana. *The American Economic Review*, 100(1), 35-69.

Devoto, F., Duflo, E., Dupas, P., Parienté, W., & Pons, V. (2012). Happiness on tap: Piped water adoption in urban Morocco. *American Economic Journal: Economic Policy*, 4(4), 68-99.

DIVUTEC. (2010). Relatório de Inquérito sobre Famílias em Situação de Pobreza e Vulnerabilidade em Bambadinca.

Filmer D, & Pritchett LH. (2001). Estimating wealth effect without expenditure data – or tears: an application to educational enrolments in states of India. *Demography* 38: 115–32.

Gaunt, C. T. (2005). Meeting electrification's social objectives in South Africa, and implications for developing countries. *Energy Policy*, 33(10), 1309-1317.

Hirmer, S., & Cruickshank, H. (2014). The user-value of rural electrification: An analysis and adoption of existing models and theories. *Renewable and Sustainable Energy Reviews*, 34, 145-154.

Houweling, T. A., Kunst, A. E., & Mackenbach, J. P. (2003). Measuring health inequality among children in developing countries: does the choice of the indicator of economic status matter? *International journal for equity in health*, 2(1), 1.

Howe, L. D., Hargreaves, J. R., & Huttly, S. R. (2008). Issues in the construction of wealth indices for the measurement of socio-economic position in low-income countries. *Emerging themes in epidemiology*, 5(1), 1.

Isham, J. (2002). The effect of social capital on fertiliser adoption: Evidence from rural Tanzania. *Journal of African economies*, 11(1), 39-60.

Jiayi, H., Chuanwen, J., & Rong, X. (2008). A review on distributed energy resources and MicroGrid. *Renewable and Sustainable Energy Reviews*, 12(9), 2472-2483.

Kemmler, A. (2007). Factors influencing household access to electricity in India. *Energy for Sustainable Development*, 11(4), 13-20.

Kirubi, C., Jacobson, A., Kammen, D. M., & Mills, A. (2009). Community-based electric micro-grids can contribute to rural development: evidence from Kenya. *World Development*, 37(7), 1208-1221.

Kivaisi, R. T. (2000). Installation and use of a 3 kW p PV plant at Umbuji village in Zanzibar. *Renewable Energy*, 19(3), 457-472.

Kremer, M., & Miguel, E. (2007). The Illusion of Sustainability. *Quarterly Journal of Economics*. Vol. CXXII No. 3. August.

Krishna, A., & Shrader, E. (2000). Cross-cultural measures of social capital: a tool and results from India and Panama. *Social capital initiative working paper*, 21.

Lee, K., Miguel, E., & Wolfram, C. (2016). Experimental Evidence on the Demand for and Costs of Rural Electrification: National Bureau of Economic Research.

Louw, K., Conradie, B., Howells, M., & Dekenah, M. (2008). Determinants of electricity demand for newly electrified low-income African households. *Energy Policy*, 36(8), 2812-2818.

Mansuri, G., & Rao, V. (2004). Community-based and-driven development: A critical review. *The World Bank Research Observer*, 19(1), 1-39.

McEachern, M., & Hanson, S. (2008). Socio-geographic perception in the diffusion of innovation: Solar energy technology in Sri Lanka. *Energy Policy*, 36(7), 2578-2590.

McKenzie, D. (2003). Measure inequality with asset indicators. Cambridge, MA: Bureau for Research and Economic Analysis of Development. *Center for International Development, Harvard University*.

Moharil, R. M., & Kulkarni, P. S. (2009). A case study of solar photovoltaic power system at Sagardeep Island, India. *Renewable and Sustainable Energy Reviews*, 13(3), 673-681.

Nouni, M., Mullick, S., & Kandpal, T. (2006). Photovoltaic projects for decentralized power supply in India: a financial evaluation. *Energy Policy*, 34(18), 3727-3738.

Prasad. (2006). Social issues. In: Winkler, H. (Ed.), *Energy Policies for Sustainable Development in South Africa: Options for the Future*, first ed. *Energy Research Centre, Cape Town (Chapter 5)*.

Putnam, R. D., Leonardi, R., & Nanetti, R. Y. (1994). *Making democracy work: Civic traditions in modern Italy*: Princeton university press.

Rao, M. N., & Reddy, B. S. (2007). Variations in energy use by Indian households: an analysis of micro level data. *Energy*, 32(2), 143-153.

Reddy, B. S., & Srinivas, T. (2009). Energy use in Indian household sector—An actor-oriented approach. *Energy*, 34(8), 992-1002.

RGPH. (2009). Recenseamento Geral da População e Habitacão 2009

Rolland, S., & Glania, G. (2011). Hybrid mini-grids for rural electrification: lessons learned. *Alliance for Rural Electrification (ARE), Brussels, Belgium, Mar.*

Sahn, D. E., & Stifel, D. (2003). Exploring alternative measures of welfare in the absence of expenditure data. *Review of Income and Wealth*, 49(4), 463-489.

Schillebeeckx, S. J., Parikh, P., Bansal, R., & George, G. (2012). An integrated framework for rural electrification: Adopting a user-centric approach to business model development. *Energy Policy*, 48, 687-697.

Ulstrup, K., Winther, T., Palit, D., Rohracher, H., & Sandgren, J. (2011). The solar transitions research on solar mini-grids in India: Learning from local cases of innovative socio-technical systems. *Energy for Sustainable Development*, 15(3), 293-303.

Vyas, S., & Kumaranayake, L. (2006). Constructing socio-economic status indices: how to use principal components analysis. *Health policy and planning*, 21(6), 459-468.

Walekhwa, P. N., Mugisha, J., & Drake, L. (2009). Biogas energy from family-sized digesters in Uganda: Critical factors and policy implications. *Energy Policy*, 37(7), 2754-2762.

Woolcock, M. (1998). Social capital and economic development: Toward a theoretical synthesis and policy framework. *Theory and society*, 27(2), 151-208.

World Energy Outlook. (2011). *Energy for All Paris, France: OECD/IEA*.

10. Appendix

10.1 Explanation of variable names used in regressions

Definition	
Log distance	The natural logarithm of distance to the grid in meters
Number of adults	Number of adults in household
Female head	Dummy; 1= household has a female head
Private business	Dummy; 1= household is running a private business
Fridge	Dummy; 1= household owns a Fridge
TV	Dummy; 1= household owns a TV
Generator	Dummy; 1= household used a generator frequently prior to the service
Badora	Dummy; 1= household used the service of Badora prior to the service
Lower medium income level	Dummy; 1=household belongs to the medium income category
Upper medium income level	Dummy; 1=household belongs to the upper medium income category
Richest income level	Dummy; 1=household belongs to the richest income category
Owner of house	Dummy; 1=household owns their house
Neighbourhood 2	Dummy; 1=household lives in neighbourhood 2
Participation	Dummy; 1=household participated in the of the service in some capacity other than the construction of the mini-grid
Trust neighbours	5-point scale; 1=respondent reported to distrust people from the neighbourhood a lot 5=respondent reported to trust people from the neighbourhood a lot.
30 meters	Dummy; 1=household is located 30 meters away from the grid
Trust neighbours *30meters	Interaction between 'Trust neighbours' and '30 meters'
Trust neighbours *Log distance	Interaction between 'Trust neighbours' and 'Log distance'

10.2 Income indicator

In this study the collection of accurate income data has not been possible due to the fact that very few households receive a stable income. This is a common problem in developing country research (Sahn & Stifel, 2003). A number of methods have been suggested in order to overcome this limitation and classify households according to their socio-economic status. One method is to measure a household's consumption expenditure. Another method is to create asset based indicators. Although some issues exist with the method of asset based indicators (inability to incorporate short run shocks or the potential varying quality of included assets, inability to compare the same assets between different cities or countries) this method is thought to reduce the number of biases linked to the consumption expenditure method (measurement errors like recall bias, seasonality of consumption, and time considerations) (See Vyas & Kumaranayake, 2006 for a discussion).

This study is therefore following the asset based method to proxy for household socio-economic status whereby information of possession of a number of durable assets and household characteristics were used in order to create an indicator using principal component analysis (PCA) (Filmer D & Pritchett LH., 2001; McKenzie, 2003)³⁴. Households were then assigned to four socio-economic groups accordingly: the poorest income group, the lower medium income group, the upper medium income group and the richest income group.

PCA is a descriptive technique that summarizes variables which are correlated. More specifically PCA creates uncorrelated variables, the principal components, which are linear weighed combinations of the initial variables they represent. This method allows to represent correlated variables with one variable, the principal component, which contains most of the information of the original variables, and to investigate patterns of associations between them (See Bartholomew, Steele, Galbraith, & Moustaki, 2008 for a description).

P observed variables x_i ($1 = 1, 2, 3, \dots p$) are elicited for each unit, which are correlated with each other with a total variance:

$$\text{var}(x_1) = \text{var}(x_2) + \dots \text{var}(x_p)$$

³⁴ PCA is a method used for continuous data and therefore using it for discrete data is seen as a limitation. Multiple Correspondence Analysis (MCA) is similar to PCA, but it is for discrete data and a number of studies use MCA instead of PCA to construct asset based indexes. However, studies have found that these two measures give very similar results (Boysen, Van Der Berg, Burger, Von Maltitz, & Du Rand, 2008; in Howe, Hargreaves, & Huttly, 2008). This was confirmed in this study as well. PCA was used in this study as recommended by Howe and co authors (Howe et al., 2008).

The principal components y_j ($j = 1, 2, \dots, p$) are linear weighted combinations of the initial variables. The weights derive from the eigenvalue decomposition of the correlation (or if the original variables are standardized from covariance matrix) of x_1, \dots, x_p . $var(x_j)$ is the j th eigenvalue and $(a_{1j}, a_{2j} \dots a_{pj})$ the analogous eigenvector (weights).

$$y_1 = a_{11}x_1 + a_{21}x_2 + \dots + a_{p1}x_p$$

$$y_2 = a_{12}x_1 + a_{22}x_2 + \dots + a_{p2}x_p$$

.

$$y_3 = a_{13}x_1 + a_{23}x_2 + \dots + a_{p3}x_p$$

The following constraints apply:

$$\sum_{i=1}^p a_{ij}^2 = 1 \quad (j = 1, 2, \dots, p)$$

$$\sum_{i=1}^p a_{ij} a_{ik} = 0 \quad (j \neq k; j = 1, \dots, p; k = 1, \dots, p)$$

$$\sum_{j=1}^p var(y_j) = \sum_{i=1}^p var(x_i)$$

The principal components are derived in declining variance with the first component capturing the largest level of variation of the original data. For constructing the asset based index, it is usually assumed that the first principal component provides a measure of income level (see Vyas & Kumaranayake, 2006 for a discussion). The weights or factor scores for each indicator from this first principal component, are used to generate a household score, which has a mean equal to zero, and a standard deviation equal to one. The higher the score the higher the socio-economic status of the household.

Table 1 lists the summary statistics of the characteristics of the households and their possessions, which were used to classify (prior to consultation with the community) the households according to their socio-economic status, as well classifying the corresponding factor scores of the first principal component derived from the PCA. This principal component explains 22.46% of the variance. In other studies this has been found to range from 12% (Houweling, Kunst, & Mackenbach, 2003) to 27% (McKenzie, 2003) (discussed in Vyas & Kumaranayake, 2006). Generally, a variable with a positive factor score is associated with

higher socio-economic status, and conversely a variable with a negative factor score is associated with lower socio-economic status.

TABLE 1 DESCRIPTIVE STATISTICS OF VARIABLES USED TO CREATE INCOME INDICATOR AND THEIR CORRESPONDING FACTOR SCORES

Household roof	Factor scores	Possessions	Factor scores		
Straw	9.6%	-0.3662	Bike	60.35%	0.0557
Zinc	89.9%	0.3399	Motorbikes	20.71%	0.2064
Tiles	0.51%	0.0767	Cars	9.87%	0.1989
Household construction	Factor scores	Floor	Factor scores		
Definitive	1.26%	0.1168	Mosaic	1.26%	0.0790
Precarious	91.92%	-0.3082	Cement	61.36%	0.4323
Precarious with improvements	6.82%	0.2815	Mud	37.37%	-0.4534
Main water resource	Factor scores	Household cooking fuel	Factor scores		
Domestic connection	0.25%	Coal	41.67 %		
ACDB fountain	50.89%	Biomass	49.75 %		
Fountain other	17.72 %	Coal and biomass	8.08 %		
Well	30.63%	Gas	0.25 %		
Other	0.51%	Gas and Coal	0.25 %		

As expected living in a house with a roof made of straw and a mud floor, a precarious construction, using water from the well³⁵ as a primary drinking source, using biomass³⁶ as a main cooking fuel, and not possessing motorbikes and cars, are all associated with a lower socio-economic status. Whereas living in a house with tiles or zinc on the roof or cement or mosaic on the floor, a definitive or a non-definitive construction with improvements, possessing a car or a motorbike and using coal or a combination of coal and biomass, or coal and gas, are all associated with a higher socio-economic status.

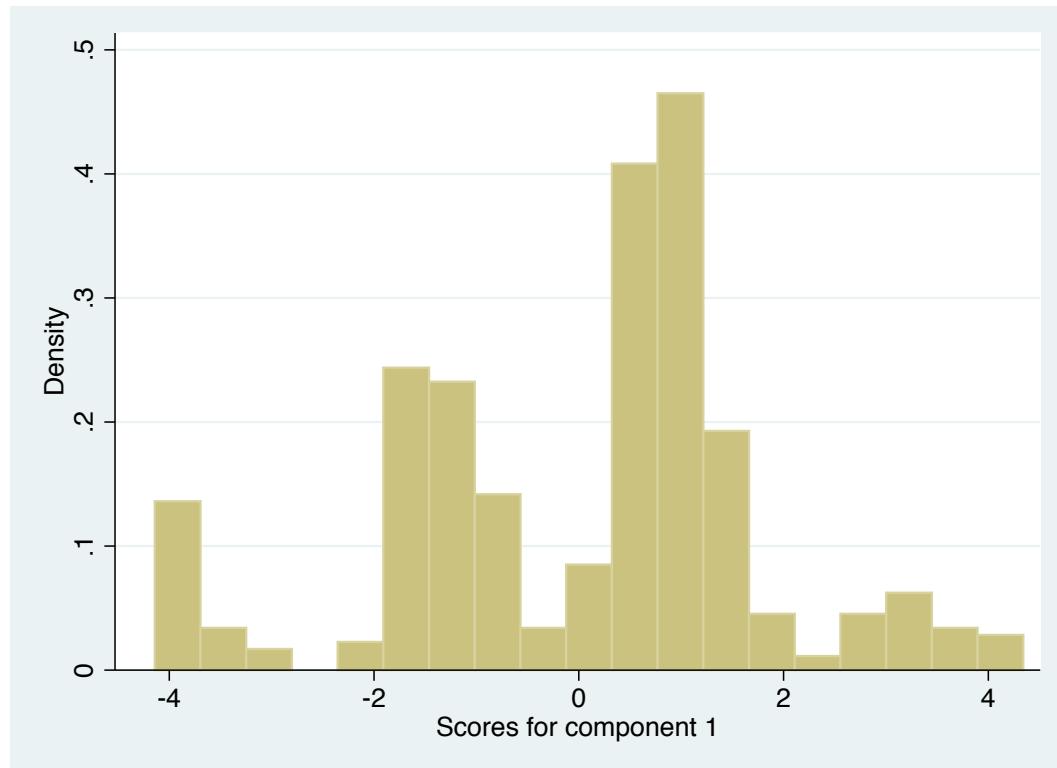
As discussed by Vyas & Kumaranayake, 2006 two limitations with using PCA to create income indicators are clumping, whereby households are not evenly distributed but are grouped together in small clusters, and truncation, whereby households are only distributed

³⁵ In the case of the main drinking water source only the distinction between drinking water from the well or from another source was introduced in the PCA (as differences between all other sources largely depend on geographical location of the household and not on socio-economic level).

³⁶ As in the case of water; cooking fuels were introduced in the PCA as a binary variable distinguishing between households who only use biomass and households who use coal or a combination of coal and biomass or coal and gas.

amongst a limited scope. The following histogram demonstrates that although the distribution of the derived socio-economic scores are not perfectly normal, there are also no serious indications of clumping and truncation.

FIGURE 1 DISTRIBUTION OF SOCIO-ECONOMIC SCORES DERIVED FROM PRINCIPAL COMPONENT ANALYSIS



The socio-economic score generated for each household was not included in the regression, but it was divided into four roughly equal categories (quartiles) for further analysis, representing the poorest, the lower medium, the upper medium and the richest groups of the community (there is a variety of ways these classifications are done see Vyas & Kumaranayake, 2006 for a discussion). Table 2 lists the mean socio-economic score of each income group.

TABLE 2 MEAN SOCIO-ECONOMIC SCORE OF DIFFERENT INCOME GROUPS

	Poorest	Lower medium	Upper medium	Richest
Score	-2.23	-0.21	0.80	2.04

Overall, the number of variables used to derive this asset indicator is smaller than in most studies (usually it ranges from 10 to 30 see Vyas & Kumaranayake, 2006 for a discussion). A number of additional variables often used in income classification exercises such as education and gender of household head, receiving remittances from abroad, receiving a fixed salary as well as possession of energy durables, were not introduced in the PCA in order to study their effect on the household's decision to connect to the mini-grid separately.

10.3 Other questions on integration in the community and participation in the project

At the time of the survey, knowledge in the community regarding the service was high. 98% of respondents stated that they knew about the project. The grand majority was informed informally through family, friends and neighbours and less from the marketing campaign undertaken by project implementers. However, much less people had more informed knowledge about the service, as measured by the ability to name one of the project implementers. 33 % of surveyed households had a member who actively participated in the project (the majority of which participated in construction (28%) and much fewer (5%) participated only in an activity related to the administration or technical implementation of the project.

TABLE 3 QUESTIONS ABOUT THE PROJECT

Respondent knows about the service	97.98%	Respondent can name project facilitators?	16.41%
How did respondent find out about the service		ACDB	61.54%
Family	17.53%	Divutec	61.54%
Friends	21.65%	TESE	50.77%
Neighbours	23.20%	University of Lisbon	9.23%
Market	2.06%	DRE	1.54%
Newspaper	0.26%	Other (Portugal, EU, SNV)	12.3%
Radio	15.98%	Respondent has visited the mini-grid station	56.81%
Television	0.52%	Family member worked for the mini-grid ³⁷	33.33%
Groups/Associations	0.26%	Focus group A	2.31%
Community leaders	1.55%	Focus group B	6.92%
DIVUTEC	4.38%	Group of influence	2.31%
ACDB	3.61%	Construction	83.08%
Posters	2.06%	ACDB administration	3.08%
Other ³⁸	8.51%	Technical administration team	1.54 %
		Do not know what exactly	2.31%
		Family member worked for the mini-grid station ³⁹	4.87%
		Participation in construction	28.03%

³⁷ Focus group A, Focus group B and Group of influence, are community groups that were formed in order to inform the implementation process. Group of influence included influential people within the community including community chiefs and religious leaders. Focus group A worked closely with the group of influence in order to ensure community participation in decisions about the projects. Focus group B represented the community in work undertaken by DIVUTEC.

³⁸ Majority of other probably is from TESE, ACDB or DIVUTEC as respondents referred vaguely to a meeting.

³⁹ Apart from construction and don't know.

Bambadinca scores high on indicators, concerning participation and solidarity within the community. The majority of the respondents have participated at least once in a collective action for the benefit of the community, in addition 44% of surveyed households have at least one member who is a member of a community organisation. The grand majority also reported to have at least one person to turn to when they are in need of money.

TABLE 4 OTHER SOCIAL CAPITAL QUESTIONS

Have you ever worked for the benefit of the community?	
Never	43.43%
Once	12.63%
Sometimes	27.27%
Always	16.67%
Who do you rely on for money in time of need?	
No one	21.97%
Do not know/never had to	2.77%
Friends	65.77%
Family	38.26%
Neighbours	12.08%
Community leaders	1.34%
Religious leaders	2.68%
Other	2.68%
Someone in the household is a member of an organisation in the community	
	43.69%

10.4 Additional maps

FIGURE 2 REPRESENTATION OF THE DIFFERENT NEIGHBOURHOODS (BAIRROS) OF BAMBADINCA

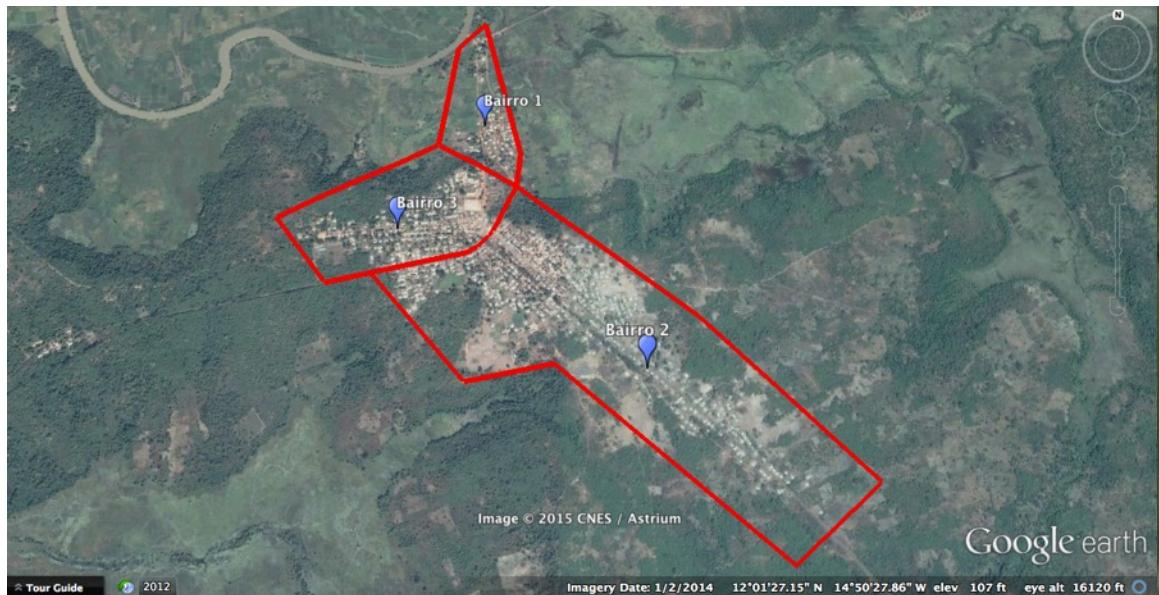


FIGURE 3 FINALIZED MAIN GRID AFTER THE TWO PHASES OF EXTENSION



RED LINES: INITIAL GRID, YELLOW LINES: FIRST EXTENSION STAGE (SUMMER OF 2015), WHITE LINES: SECOND EXTENSION STAGE (SPRING OF 2016)

FIGURE 4 REPRESENTATION OF THE DIFFERENT ZONES (ZONAS) OF BAMBADINCA

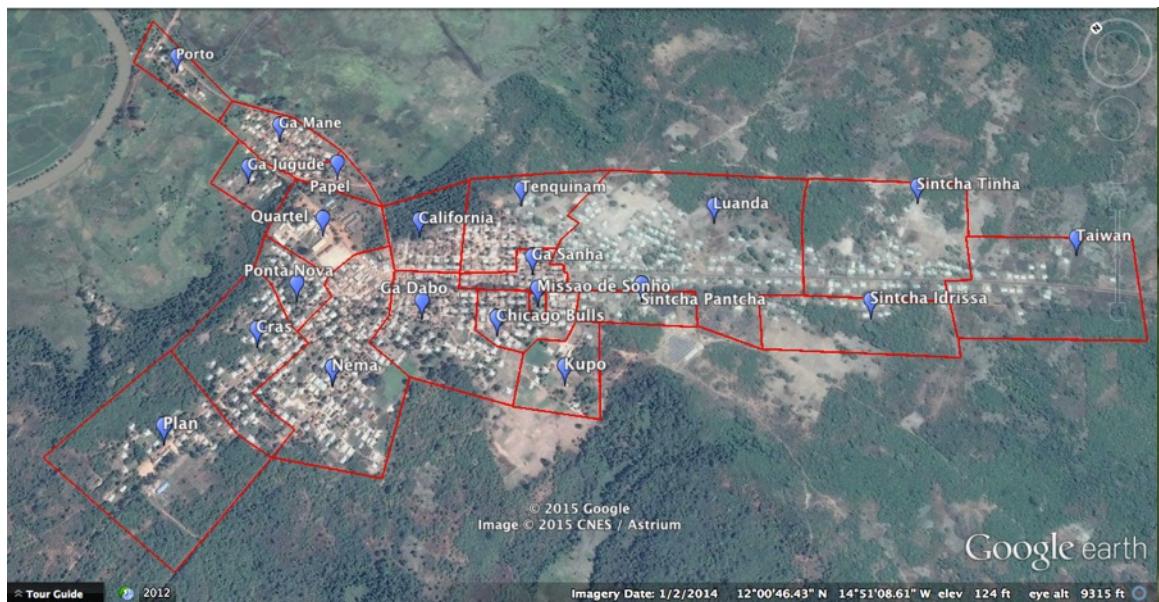
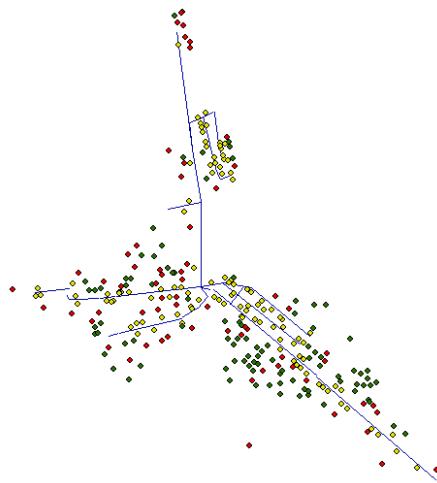


FIGURE 5 MAP OF CONNECTION PATTERNS OF ALL CONNECTED HOUSEHOLDS UNTIL NOVEMBER 2015



Households in yellow represent connected households who are situated less than 30 meters away from the grid. None of these households benefited from their neighbours' infrastructure to connect to the grid. Households in red represent connected households who are situated more than 30 meters away from the grid and did not benefit from their neighbours' infrastructure to connect to the service. Households in green represent connected households who are situated more than 30 meters away from the grid and benefited from their neighbours' infrastructure to connect to the service.

1. Introduction

Choice of who to interview (note to interviewer):

- Present yourself briefly
- Ask: "Who makes the financial decisions, pays for the energy bills and makes the decision regarding the purchase of energy products in this household? Can I talk to this person?"
- If not available ask: "When can I come back to talk to that person?"
- If not possible to talk to this person especially if this person does not want to be interviewed or if someone else in the family prefers to respond to the survey try to insist and underscore that the participation of this person to this survey is very important to us in order to get the right information
- As a last resort agree to talk to someone who is well informed of the household's daily activities and forms an important part in the household's decision making process

Note to interviewer:

After you have established who to talk to communicate the following information:

We are conducting a survey in your community as part of a research project undertaken by a PhD student at London School of Economics and Political Science a University in London. The intention of this research is to understand what factors affect the adoption of the new energy service that will be provided soon to your community. This service is promoted by TESE, ACDB, Divutec and University of Lisbon. We have randomly chosen a number of households in Bambadinca to participate in this survey and your household is amongst the ones selected.

The survey consists of questions about how you are living, what type of energy you are consuming and your opinion about certain issues regarding your daily activities and your community. These questions should take around one hour to complete. Your answers will be strictly confidential and will not be shared with anyone else. Answers will only be used anonymously for research purposes. The information generated by the study may be published, but no details will be released from which the participant could be identified. Participation is voluntary you can refuse to participate without providing any explanation and without any

consequences. If you agree to participate in the survey you have the right to stop whenever you want.

Your participation is very important to us. We will use the information you and other families give us to better understand the factors that affect the success of the new electricity project and advance academic knowledge and inform future energy policies in Guinea-Bissau.

Do you have any questions? May I continue with interviewing you?

Your responses will not have any effect on the way the service will be provided. It is important that you give us honest responses. If the information that we collect is not correct the results of our research will not benefit Bambadinca nor Guinea-Bissau.

(Note to the interviewer: Isolate the interview before beginning the survey)

Household number	
Zone number	
Note to interviewer: are you speaking with the person who makes the financial decisions and decisions regarding the purchase of energy products in this household?	Yes No Other. Specify _____
How many households share this building including yours?	
What are the names of the other household heads?	
What is your Mobile number? <u>(Note to interviewer:</u> After you ask for the mobile number inform the respondent that the survey supervisor might be calling just to check if the survey was conducted properly)	

What is your name?	
What is the gender of the respondent?	Female Male
What is your age? <u>(Note to interviewer:</u> If they do not know their age or if they seem to be giving you the wrong answer take a note of the age they seem to have. As a clue, ask them what is the age of their eldest son)	
What is your education level?	No education Primary education Secondary education Higher education Other. Specify _____
Are you the household head?	Yes No

Note to interviewer: ask the following questions if respondent is not the household head

What is the name of the household head?	
What is the gender of the household head?	Female Male
What is your relationship with the household head?	
What is the age of the household head?	

2. Socio-economic questions

Note to interviewer: Start this section by saying: “I will begin by asking you a few questions on the demographic and socio-economic characteristics of your family, your activities the house where you live in and the things you possess”.

How many people live in this household including you? By household I mean all individuals who normally live and eat their meals together in this household and share their expenses. (<u>Note to interviewer:</u> Here in order to make sure we get the right response make sure to make a short conversation about what the relationship of each member is to the respondent. Example: Begin by asking who else lives here)	
What is the ethnicity of the household?	Fula Mandinga Balanta Beafada Papel Cabo-Verde Other. Specify _____
What is the religion of the household?	Muslim Christian Animist Other. Specify _____
How many household members are between 0-16 years old?	
Do you have children that are currently attending school?	Yes No
How many years has your household lived in Bambadinca?	
What is the highest level of education in this household?	No education Primary education Secondary education Higher education Other. Specify _____
What is the principal economic activity of your household?	Public servants. Specify _____ Private employees. Specify _____ Services/ Commerce. Specify _____

(Note to interviewer: you can note more than one)	Agriculture. Specify _____ Fishing. Specify _____ Animals. Specify _____ Other. Specify _____
Did individuals in your household operate commercial activities over the past month? (Note to interviewer: if 'No' move to the following page)	Yes No
If 'Yes' what type of commercial activity?	
Where do you operate the enterprise?	Home, inside residence Home, outside residence Traditional market Commercial area shop Roadside Other fixed place Mobile
Do you use electricity for your enterprise?	Yes No
Does any member of the family receive a fixed salary?	Yes No
Is your household negatively affected during the months when there is less income availability in the community? (August, September, October)	Not at all A little bit A lot
Does your household receive money from abroad?	Yes No
At this moment what is your family's expenditure (FCFA) in: (Note to interviewer: start by asking about daily expenses)	
Food	Per day _____ Per week _____ Per month _____ Other. Specify _____
Water	Per day _____ Per week _____ Per month _____ Other. Specify _____
Transport	Per day _____ Per week _____ Per month _____

	Other. Specify _____
Communications	Per day _____ Per week _____ Per month _____ Other. Specify _____
Health	Per day _____ Per week _____ Per month _____ Other. Specify _____
Education	Per day _____ Per week _____ Per month _____ Other. Specify _____
Entertainment	Per day _____ Per week _____ Per month _____ Other. Specify _____
Clothes and shoes	Per day _____ Per week _____ Per month _____ Other. Specify _____
Other	Per day _____ Per week _____ Per month _____ Other. Specify _____

What is the type of ceiling in this household unit? (<u>Note to interviewer:</u> answer this question on your own through observation)	Straw Zinc Other. Specify _____
What is the construction type of this household unit? (<u>Note to interviewer:</u> answer this question on your own through observation)	Definitive Precarious Precarious improved Hut Other. Specify _____
What is the material used on the pavement of this household unit?	Mosaic Cement

	Mud Other. Specify_____
This household unit is:	Occupied by the owner Rented Borrowed Other. Specify_____
What main source of drinking water does your household use?	Domestic connection ACDB fountain Other fountain Well Other. Specify_____
Do you have bicycles in your household?	Yes No
If 'Yes' how many bicycles?	
Do you have motorbikes in your household?	Yes No
If 'Yes' how many motorbikes?	
Do you have cars in your household?	Yes No
If 'Yes' how many cars?	

3. Energy use questions

Note to interviewer: Start this section by saying: "Now I would like to ask some questions concerning the use of energy in your household."

Do you use candles in your household? (<u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many hours per day do you use candles? (<u>Note to interviewer:</u> make sure to ask for the whole household. If some candles are used less than others make a note).	Lighting_____ Other_____ Cannot Say
In what units do you purchase these candles?	Individual Box. Specify quantity_____
What sizes do you usually purchase?	Small Medium Large Other. Specify_____

What is the price per unit of this(these) size(s)?	Small _____ Medium _____ Large _____ Other. Specify _____
How many units of candles does your household consume (<u>Note to interviewer</u> : they can respond per day, week or other, make a note accordingly)	
Small	Per day _____ Other _____
Medium	Per day _____ Other _____
Large	Per day _____ Other _____
Other size	Per day _____ Other _____

Do you use radios in your household? (<u>Note to interviewer</u> : If 'No' move to the next page)	Yes No
How many radios do you have?	

How do these radios operate?	Electricity Batteries Other. Specify _____
How do you choose your radios?	Price Duration Number of batteries Size of batteries USB portal Size Quality of sound Appearance Other _____
How many hours per day do you use these radios?	With batteries _____ With electricity _____ With other _____ Can't tell
(Note to interviewer: Continue this section only if the household uses radios that operate with batteries if 'No' move to the following section)	
In what units do you purchase the batteries?	Charge (2 batteries) Box (12 batteries) Other _____
What battery sizes do you usually purchase for your Radios? (Nota to interviewer: Specify for each radio)	
Radio 1	Small Medium Large Other. Specify _____
Radio 2	Small Medium Large Other. Specify _____
	Small Medium Large Other. Specify _____

Radio 3	Small _____ Medium _____ Large _____ Other. Specify _____
Radio 4	Small _____ Medium _____ Large _____ Other. Specify _____
Other radios	Small _____ Medium _____ Large _____ Other. Specify _____
What is the price per unit of this(these) size(s)?	Small _____ Medium _____ Large _____ Other _____
How many batteries each of the radios takes? <u>Note to interviewer:</u> take a note for each radio individually)	Radio 1 _____ Radio 2 _____ Radio 3 _____ Radio 4 _____ Other radios _____
How long do these batteries last? <u>Note to interviewer:</u> take a note for each radio. <u>Note to interviewer:</u> they can respond per day, per week or other, make a note accordingly)	Per day _____ Per week _____ Other _____
Radio 1	Per day _____ Per week _____ Other _____
Radio 2	Per day _____ Per week _____ Other _____
Radio 3	Per day _____ Per week _____ Other _____
Radio 4	Per day _____ Per week _____ Other _____

Other radio	Per day _____
	Per week _____
	Other _____

Do you use flash lights in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many flash lights do you use?	
How do these flash lights operate?	Electricity _____ Batteries _____ Other. Specify _____
How do you choose your flashlights?	Price Duration Number of batteries Size of batteries Quality of illumination Size Appearance Other _____

How many hours per day do you use these flashlights?	Flashlight 1 _____ Flashlight 2 _____ Flashlight 3 _____ Flashlight 4 _____ Other flashlight _____ Can't tell
(Note to interviewer: Continue this section only if the household uses flash lights that operate with batteries if 'No' move to the following section)	
In what units do you purchase the batteries?	Charge (2 batteries) Box (12 batteries) Other _____
What battery sizes do you usually purchase for your flashlight? (Note to interviewer: Specify for each flashlight)	
Flashlight 1	Small Medium Large Other. Specify _____
Flashlight 2	Small Medium Large Other. Specify _____
Flashlight 3	Small Medium Large Other. Specify _____
Flashlight 4	Small Medium Large Other. Specify _____
Other flashlight	Small Medium Large Other. Specify _____

What is the price per unit of this(these) size(s)?	Small _____ Medium _____ Large _____ Other _____
How many batteries each of the radios takes? (<u>Note to interviewer:</u> take a note for each radio individually)	Flashlight 1 _____ Flashlight 2 _____ Flashlight 3 _____ Flashlight 4 _____ Other flashlight _____
How long do these batteries last? (<u>Note to interviewer:</u> take a note for each flashlight. <u>Note to interviewer:</u> they can respond per day, per week or other, make a note accordingly)	
Flashlight 1	Per day _____ Per week _____ Other _____
Flashlight 2	Per day _____ Per week _____ Other _____
Flashlight 3	Per day _____ Per week _____ Other _____
Flashlight 4	Per day _____ Per week _____ Other _____
Other flashlight	Per day _____ Per week _____ Other _____

Do you use battery powered lamps in your household? (<u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many battery powered lamps do you use?	
How many hours per day do you use these battery powered lamps?	Lamp 1 _____ Lamp 2 _____ Lamp 3 _____ Lamp 4 _____ Other lamp _____ Can't tell
In what units do you purchase the batteries?	Charge (2 batteries) Box (12 batteries) Other _____
What battery sizes do you usually purchase for your lamps? (<u>Note to interviewer:</u> Specify for each radio)	

Lamp 1	Small _____ Medium _____ Large _____ Other. Specify _____
Lamp 2	Small _____ Medium _____ Large _____ Other. Specify _____
Lamp 3	Small _____ Medium _____ Large _____ Other. Specify _____
Lamp 4	Small _____ Medium _____ Large _____ Other. Specify _____
Other lamp	Small _____ Medium _____ Large _____ Other. Specify _____
What is the price per unit of this(these) size(s)?	Small _____ Medium _____ Large _____ Other _____
How many batteries each of the lamps takes? <u>Note to interviewer:</u> take a note for each radio individually	Lamp 1 _____ Lamp 2 _____ Lamp 3 _____ Lamp 4 _____ Other lamp _____
How long do these batteries last? <u>Note to interviewer:</u> take a note for each lamp. <u>Note to interviewer:</u> they can respond per day, per week or other, make a note accordingly)	

Lamp 1	Per day _____ Per week _____ Other _____
Lamp 2	Per day _____ Per week _____ Other _____
Lamp 3	Per day _____ Per week _____ Other _____
Lamp 4	Per day _____ Per week _____ Other _____
Other lamp	Per day _____ Per week _____ Other _____

Do you use batteries in your household for other equipment apart from radio, flashlight and battery powered lamps? (<u>Note to interviewer</u> : If 'No' move to the next page)	Yes No
What do you use these batteries for?	
How many hours per day do you use this equipment?	
In what units do you purchase the batteries?	Charge (2 batteries) Box (12 batteries) Other _____
What battery sizes do you usually purchase for your lamps? (<u>Note to interviewer</u> : Specify for each equipment)	Small _____ Medium _____ Large _____ Other _____

What is the price per unit of this(these) size(s)?	Small _____ Medium _____ Large _____ Other _____
How many batteries each equipment consumes? (<u>Note to interviewer:</u> take a note for each individually. <u>Note to interviewer:</u> they can respond per day, per week or other, make a note accordingly)	Per day _____ Per week _____ Other _____

What is the main source of cooking used in your household?	Firewood Coal Other. Specify _____
How much do you pay?	Per day _____ Per week _____ Other _____

In the past were you connected to the grid?	Yes No Other _____
Are you using the Badora service now?	Yes No
If 'No' were you using the Badora service in the past?	Yes No
Are you using electricity from another private provider?	Yes. Specify _____ Other _____
(<u>Note to interviewer:</u> If household is not currently using Badora or the service of another private provider pass to the following page)	
If 'Yes' what is your monthly expenditure?	
If 'Yes' what were your connection costs?	
Do you sell electricity services to your neighbours?	Yes No

(Note to interviewer if 'No' move to the following page)	
If 'Yes' what type of services?	Electricity Mobile charging Charging of other equipment Other. Specify _____
If 'Yes' how much do you make each month from these services?	

Do you have a generator? (Note to interviewer: If 'No' move to the following page)	Yes No
With what frequency do you use your generator?	Never Rarely Frequently Every day Other _____
(Note to interviewer: If 'Never' or 'Rarely' move to the following page)	
How much do you spend each month in Gasoline (FCFA)?	
How much do you spend each year in maintenance for the generator?	
Do you sell electricity services to your neighbours? (Note to interviewer if 'No' move to the following page)	Yes No
If 'Yes' what type of services?	Electricity Mobile charging Charging of other equipment Other. Specify _____
If 'Yes' how much do you make each month from these services?	

Do you use other sources of energy in your household apart from the ones mentioned above? (if 'No', move to the following page)	Yes No
Which ones? (Specify)	
How many hours per day?	
In what units do you usually purchase them?	
What is the price per unit?	
How many units does your household normally consume? (<u>Note to interviewer</u> : the can respond per day, per week or other, take a note accordingly)	
Do you have mobile phones in your household?	Yes No
How many mobile phones does the household have?	
Where do you charge them?	At home Neighbour Store Other. Specify _____
Do you pay to charge them? (<u>Note to interviewer</u> : If 'No' go to the next section)	Yes No
How much do you pay to charge one?	

Do you have lamps in your household? (<u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many lamps do you have?	
These lamps are normal or efficient?	Normal Efficient Other
How many hours per day do you use these lamps? (<u>Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these lamps operate?	Generator Private operator Other _____

Do you have televisions in your household? (<u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many televisions do you have?	
How many hours per day do you use these televisions? (<u>Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these televisions operate?	Generator Private operator Other _____

Do you have fans in your household? (<u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
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How many fans do you have?	
How many hours per day do you use these fans? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these fans operate?	Generator Private operator Other _____

Do you have fridges in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many fridges do you have?	
How many hours per day do you use these fridges? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these fridges operate?	Generator Private operator Other _____

Do you have computers in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many computers do you have?	
How many hours per day do you use these computers? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

How do you make these computers operate?	Generator Private operator Stores Neighbours Other _____
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Do you have electric irons in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many electric irons do you have?	
How many hours per day do you use these electric irons? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these electric irons operate?	Generator Private operator Other _____

Do you have satellite dishes in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many satellite dishes do you have?	
How many hours per day do you use these satellite dish? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these satellite dish operate?	Generator Private operator Other _____

Do you have DVDs in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
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How many DVDs do you have?	
How many hours per day do you use these DVDs? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these DVDs operate?	Generator Private operator Other _____

Does your household possess other equipment? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
Specify	
Quantity	
How many hours per day do you use these equipment? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell
How do you make these equipment operate?	Generator Private operator Other _____

4. Questions about 'Bambadinca Sta Claro'

Do you know about the new energy service that will be available briefly in Bambadinca? (the 'Bambadinca Sta Claro' project)	Yes No
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If 'Yes' how did you find out?	Family Friends Neighbours Local market National newspaper Radio Television Groups and associations Community leaders Divutec ACDB Posters Other _____
Do you know the project partners?	Yes No Not sure
Can you name the project partners?	ACDB DIVUTEC TESE University of Lisbon General energy directory No Other _____
Have you visited the power plant?	Yes No
Did any member of your household participate actively in the project? (<u>Note to interviewer:</u> prompt if necessary)	Yes No
If 'Yes', Specify:	Focus group A Focus group B Group of influence Construction ACDB administration Technical administration team Other. Specify _____
Are you planning to connect?	Yes No Not sure _____
Has any member of your household started saving to meet the upfront connection costs of the energy service?	Yes No Not Sure

If 'Yes' which member of the family is saving? (Note to interviewer: if not respondent ask about the relationship of that person with respondent)	
If 'Yes' how are you saving?	Not saving Bank account Burra Community saving group Divutec Other. Inside the household Other. Specify _____

5. Social Capital questions

Is anyone in your household a member of any community organizations in Bambadinca? Like for example:	ACDB Conselho Islâmico Afas Bam Amus Bam Titina Silla Fans Club Lala Queima Comunidade Ingreja Evangélica Tene Diritu AJUB Amizade de Nema Wantanara Costa Largo Djokere Endan Other. Specify _____ No
Introduce by saying: "In every community, some people get along with others and trust each other, while other people do not. Now, I would like to talk to you about trust and solidarity in your community".	
Do you agree or disagree that: "Most people who live in this community can be trusted"	Agree strongly Agree somewhat Neither agree nor disagree

	Disagree somewhat Disagree strongly
Do you agree or disagree that: “I feel accepted as a member of this community”	Agree strongly Agree somewhat Neither agree nor disagree Disagree somewhat Disagree strongly
Introduce by saying: “Now I want to ask you how much you trust different types of people”	
How much do you trust people in your family?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust your friends?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust your neighbours?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust people in other neighbourhoods?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust people of other ethnicities?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust the implementers of the project ‘Bambadinca Sta Claro’?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust officials from the local government?	Trust a lot Trust Neither trust nor distrust Distrust

	Distrust a lot
How much do you trust NGOs?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
How much do you trust the traditional leaders of the community?	Trust a lot Trust Neither trust nor distrust Distrust Distrust a lot
Have you worked with others in your community to do something for the benefit of the community?	Never Once A couple of times Frequently
If you suddenly needed a small amount of money (enough to pay for expenses for your household for one week) how many people beyond your immediate household could you turn to who would be willing to provide this money?	
Who are these people?	Friends Family Neighbours Community leaders Religious leaders Other _____

Chapter 4

The role of recall periods in improving the accuracy of energy expenditure elicitation in surveys: empirical results from Guinea-Bissau

Abstract

This study tests the accuracy of reported energy expenditure in surveys when using differently defined recall periods, that is a ‘usual’ week versus a ‘specific’ (i.e. last) week. We compare real expenditure data for prepaid meters for energy from a community solar hybrid mini-grid in rural Guinea-Bissau, with answers elicited from a survey where the two different recall periods are randomly assigned. Overall, our results show that respondents tend to over-report the level and frequency of their energy expenditures, but reporting is more accurate when the ‘specific’ period rather than the ‘usual’ period is used. Expenditure specific characteristics have a stronger effect on the level of misreporting than individual and household specific characteristics. However, we find evidence that respondents that report higher dissatisfaction with the service over-report their expenditures. The level of expenditure as well as the level of irregularity of weekly payment frequency, retain a robust effect on all the different measures of error used. There is also evidence that the irregularity of weekly payment frequency affects negatively reporting error in the ‘specific’ period rather than in the ‘usual’ period, which is attributed to the use of different response strategies and their varying effects on accuracy. However, this is robust for most models of error on payment frequency reporting but less so for error on expenditure level reporting.

1. Introduction

Comprehensive information on household consumption expenditures is central to the study of a range of issues of interest to economists such as the welfare of individuals, household decision making processes, responses to policy and shocks, inequality, poverty and theories of consumption and saving. This information is even more important for developing countries where, due to lack of stable income sources, economists often rely on household expenditure information for the measurement of living standards (Deaton & Grosh, 2000). Due to a lack of administrative or third party data on household consumption (e.g. tax records, scanner data, e-commerce websites), both in developed and developing countries, economists have relied either on diary approaches (where households are asked to provide detailed information on their daily expenditures) or more commonly on expenditure surveys. This is predominantly due to their ease of implementation (see Browning, Crossley, & Winter, 2014). However, a broad literature has demonstrated that self-reported measures of expenditure are prone to a number of errors (see for reviews Browning, Crossley, & Weber, 2003; Crossley et al., 2014; Deaton & Grosh, 2000). Understanding the source of these errors and how to minimize them enables us to collect more accurate responses.

The main sources of measurement error in expenditure surveys are recall errors due to memory limitations, telescoping due to misplacing of events (or expenses), as well as social pressures, respondent effects, interviewer effects, instrument design or survey conditioning (see Deaton & Grosh, 2000 for a discussion). The study of these errors draws from the behavioural economics literature, namely the strand of behavioural economics that focuses on the effects of bounded rationality and the social context on survey reporting.

Due to computational difficulties, limited attention and biased reasoning individuals tend to simplify complex decisions through estimation strategies (Kahneman, 2003; Kahneman & Frederick, 2002; Congdon et al., 2011; Tversky & Kahneman, 1975) (see Chapter 1). In survey responses this translates to respondents often resorting to response simplification strategies that are either related to the survey instrument or to information that is available in the memory linked to the nature of the activity that they are reporting on, or both (Menon, 1993; Menon, Raghbir, & Schwarz, 1995). Social pressures and response desirability have also been linked to intentional biases of over-reporting or under-reporting in surveys (Schnell, 2013).

Studies on self-reported household expenditure errors have drawn from the abovementioned literature to identify the magnitude and sources of these errors, but also to

understand what type of interventions will lead to more accurate and efficient measures. Some of these studies have used random designs of different aspects of relevance (e.g. nature and length of recall periods, level of disaggregation of expenditures, determining who to talk to, open ended vs closed response formats and use of prompts) to isolate their effects on measurement errors (Comerford, Delaney, & Harmon, 2009). Other studies have exploited pre-existing variations in survey design caused by diverging survey practices across statistical offices or within statistical offices over time (Deaton & Grosh, 2000).

One of the major limitations of these studies is that it is usually impossible to corroborate survey responses with actual practices. Therefore, the effects of survey design are usually assessed in comparison to other self-reported measures or at best, in comparison to validation measures such as benchmarks that are believed to be closer to reality (e.g. diary approach with frequent supervision) (Beegle, De Weerdt, Friedman, & Gibson, 2012; NSSO Expert Group, 2003), or some external indicators (e.g. income, administrative and third party data) (Koijen, Van Nieuwerburgh, & Vestman, 2013; Kreiner, Lassen, & Leth-Petersen, 2013). These external indicators are however limited in developed countries and absent in developing countries.

Compared to other categories of household expenditure, information on real energy expenditure is becoming increasingly available to researchers, both in developed and developing countries (e.g. Brutscher, 2011; Qiu et al., 2016; Jack and Smith, 2016)

This provides a great opportunity to test the effect of different aspects of survey design on expenditure elicitation by using real expenditure information as a comparison. This is especially the case when it comes to energy consumption based on prepaid meters (in contrast with traditional monthly energy payments), as these expenditures have similar characteristics to other recurring household expenditures (clients control the level and frequency of their payments, which is closely connected with energy use). In addition, a better understanding of the intricacies of energy expenditure reporting and how to improve it is important as surveys are often used to inform energy, environmental and development policies and projects.

This study tests the accuracy of reported energy expenditure in surveys and how it changes when using differently defined recall periods. Specifically, a random design is used to test the effect of using the ‘usual’ week instead of a ‘specific’ week (i.e. last week) in eliciting information on the levels of energy expenditure and frequency of these purchases. We use the actual information on prepaid meter top ups from a solar-hybrid mini-grid in rural Guinea-Bissau and compare it to the survey elicited information on these expenditures.

In the ‘specific’ period, respondents are asked to state their expenses within a specific time frame, in this case the ‘last week’ (or last 7 days), whilst in the ‘usual’ period respondents are asked to state their expenses within a usual time frame, in this case a ‘usual week’. So far, theory and empirical evidence have shown the ‘specific’ period to be less demanding in terms of memory, but more prone to volatility compared to the ‘usual’ period, as it does not necessarily reflect the expenditures of a typical week (Angrisani, Kapteyn, & Schuh, 2015). The ‘usual’ period is seen to be more of a abstract concept and therefore more prone to rounding and other cognitive errors (Beegle et al., 2012). In addition a number of biases, such as anchoring, can affect responses to both periods (Comerford et al., 2009; Tourangeau, Rips, & Rasinski, 2000).

However, none of these issues have yet been corroborated with real data or in the context of energy expenditure in developing countries.

In addition, detailed knowledge about actual recent expenditure patterns allow us to closely study the potential effect of response strategies on accuracy of responses. Namely the effects of ‘recall and count’ in comparison to ‘rate based’ response strategies. ‘Recall and count’ response strategies occur when respondents resort to retrieving all the relevant events to enable them to respond to questions about frequencies or expenditure levels. ‘Rate based’ estimates occur when respondents construct a rate of occurrence of the event in question and base their responses on that rate. The latter strategy belongs to the category of simplification strategies (see Menon, 1993 for a description).

Most of the research on response strategies focuses on frequency reporting which, however, has direct application to expenditure reporting.

The choice of response strategy in survey frequency reporting for ‘specific’ periods and namely the choice between using a ‘recall and count’ or a ‘rate based’ response strategy has been found to be largely affected by the characteristics of the reported action. For example, to report infrequent behaviour, individuals undertake ‘recall and count’ strategies, whereas for frequent behaviour the degree of similarity (the degree to which reported events closely resemble one another) and regularity (the degree to which reported events occur in stable time intervals) of the action reported tends to define this strategy. In other words, individuals resort to some ‘rate based’ estimate when the actions they are reporting are more frequent, regular and similar (Tourangeau et al., 2000).

However, there is no consensus on how these estimation strategies are associated with reporting errors. Simplification strategies are by definition an approximation of the reality, but could also be seen as efficient strategies used to avoid “painstaking retrieval strategies” and

“produce better answers” (Tourangeau et al., 2000). There is also a prevalent agreement that ‘recall and count’ strategies require a higher cognitive effort (Menon, 1993; Tourangeau et al., 2000).

A number of studies have produced conflicting results (Blair & Burton, 1987; Menon, 1993). This is further complicated by the fact that it is hard to isolate the effect of the response strategy on accuracy from that of the effect of the nature of the question the respondent is answering, as the latter influences both accuracy and the choice of response strategy (Menon, 1993; Tourangeau et al., 2000). For example, Menon, 1993, finds that when it comes to frequency reporting for ‘specific’ periods, ‘rate based’ estimates are evoked for more regular and similar events. These produce more accurate responses than ‘recall and count’ strategies (Menon, 1993). However, it is not clear if this accuracy is due to the use of a ‘rate based’ estimate or to the fact that it is easier to report accurately more regular and similar events.

The nature of the reporting period has also been associated with different reporting strategies, with respondents resorting to ‘recall and count’ strategies to answer the ‘specific’ period, and to ‘rate based’ strategies to answer the ‘usual’ period (Angrisani et al., 2015). These ‘recall and count’ strategies are however not stable for the ‘specific period’, as for more similar and regular events respondents resort to ‘rate based’ estimates (Menon, 1993). This allows to isolate the effect of the reporting strategy on response error by looking at the interaction of the nature of the reporting period with the regularity and similarity of the reported activity and its effect on error. For the case of energy expenditures, regularity is assumed to be captured by the level of regularity of the weekly payment frequency. As far as similarity is concerned, all events are assumed to be similar (the payment always happens the same way in the same location).

Specifically, this study assesses the size and determinants of measurement error for energy expenditure reporting in surveys as well as the effect of using the ‘specific’ and the ‘usual’ period on the accuracy of the responses, both for the reporting of the level and the frequency of these expenditures. In addition, in order to capture the different effects that different reporting strategies have on accuracy this study tests if the level of irregularity of weekly payment frequency has a negative effect on the accuracy of the responses and if this negative effect on the accuracy of responses differs when using the ‘specific’ in comparison to the ‘usual’ period.

Results overall demonstrate that respondents tend to over-report the level and frequency of their energy expenditures and that this reporting is more accurate when the ‘specific’ period rather than when the ‘usual’ period is used. Expenditure specific characteristics are more

important than individual and household specific characteristics when it comes to misreporting. However, there is some evidence that respondents that are dissatisfied with the service over-report their expenditures. We find that the level of expenditure as well as the irregularity of weekly payment frequency retain a strong effect for all the different measures of error used. The irregularity of weekly payment frequency affects negatively measurement error in the ‘specific’ period rather than in the ‘usual’ period. This last result is an indication that ‘recall and count’ strategies are more associated with inaccuracies than ‘rate based’ estimates. However, this finding is robust for most models of error on payment frequency reporting, but less so for error on expenditure level reporting. These findings have implications for policy regarding the right choice of the recall period in survey design and the interpretation of energy expenditure information elicited by surveys.

This chapter proceeds in the following way. Section 2 provides a brief literature review. Section 3 discusses the data and the survey design. Section 4 provides the results, whilst Section 5 concludes.

2. Literature review

As noted above, some studies have looked at how different aspects of survey design can reduce errors in survey expenditure reporting by varying design characteristics or by exploring existing differences. More specifically, authors have looked into the effects of varying the nature and length of the reference period for which consumption is reported, the level of disaggregation of expenditures, response formats, as well as who to talk to and the use of survey prompts (Comerford et al., 2009). This has been done for different types of expenditures both in developed and in developing countries.

In terms of energy expenditure reporting these issues remain largely unexplored. The limited research on this topic has focused solely on developed countries. Through a field experiment Fairbrother, 2014 looks at how different ways of approaching survey participants affect their reporting regarding energy readings (compliance and data quality). Through an ex post analysis of energy expenditures responses in the British Household Panel Study (BHPS), Pudney, 2008 concludes by looking at peaks in distributions, that respondents use a number of response strategies, namely annual rounding, weekly rounding and monthly rounding. Pudney, 2008 does not attempt however to look at the effects of different aspects of survey design.

This study introduces a case study of energy expenditure reported in a developing country.

In terms of the use of ‘usual’ or ‘specific’ recall periods in expenditure reporting, studies have shown that there are some advantages and disadvantages to each method, but the literature is not proposing one particular method over the other (see Browning et al., 2014).

Previous studies indicate that responses to the ‘specific’ period tend to have an overall higher means (less forgetfulness) and larger dispersion measures (higher volatility). This indicates that the usual period gives less accurate results but is a better representation of the general trends. Angrisani et al., 2015 conduct a survey with a random design in the United States to measure among other things the effects of ‘usual’ and ‘specific’ periods on the elicitation of expenditures in surveys, and find that “the reported amounts spent were systematically lower” for the ‘usual’ periods. Results for ‘specific’ periods also exhibited higher variances. This seemed to matter more for shorter recall periods. Beegle et al., 2012 conduct a survey with a random design in Tanzania where they look at the effects of ‘usual’ and ‘specific’ periods on elicitation of household consumption by comparing them to a diary approach. Results show that the ‘usual’ period substantially reduced the accuracy of results. Neither of these studies have validated the findings by comparing them with information on

actual expenditures.

The Deaton & Grosh, 2000 review, of Living Standards Measurement Studies (LSMS) and other expenditure surveys in eliciting consumption data in developing countries, draws more conflicting conclusions. The priors about the respective impacts of the two time frames do not seem to hold, in the reporting of food expenditures, as the estimates tend to be very similar between the 'last visit' and the 'usual month' period. When there are differences, they do not conform to the expected pattern that the 'usual' month period would lead to lower means and dispersion measures. However, in the case of non-food items, that have smaller purchase frequencies, results tend to conform with priors (i.e. lower means and dispersion measures for the 'usual' month period). These small differences can be an indication that both types of reporting periods fare well, at least when it comes to reporting frequent purchases. However, these results could also be affected by the limitations of the methods used in the study in question as it is not based on a random design. In addition, the comparison between the 'last visit' and the 'general month' also differs in terms of recall period size. Finally, both periods were presented to the same respondents. Therefore, the possibility of survey conditioning and within frame anchoring cannot be ruled out (Deaton & Grosh, 2000). Despite the potential limitations of the Deaton & Grosh, 2000 study, their findings highlight the role of mediation of good specific characteristics, including purchase frequency, on the impact of the effects of the two time frames ('specific' and 'usual') for self-reported expenditure reporting in developing countries.

Our study adds to the abovementioned literature by looking at how the findings regarding the relative strength of the 'specific' and the 'usual' recall periods apply in the case of energy expenditure reporting. In addition, it is the first study to be using information on actual expenditure as a comparison. Finally, this study aims to increase comprehension about the role of the response strategy used on response accuracy.

Menon, 1993, looks at how for frequent behaviours the regularity of an event determines the response strategy used by respondents who recall the frequency by which they conducted a number of different activities the previous week (last week): more regular and similar events led to reporting a 'rate based' estimate, while irregular and dissimilar events led to a 'recall and count' estimate. This is done by directly eliciting the response strategy of each respondent (by asking respondents to explain the way they formed their responses) and combining a diary approach to check the accuracy of responses. The study finds that in this context the 'rate based' estimate gives more accurate results and is less cognitively demanding than the 'recall and count' approach. However, the increased accuracy could have been caused

by the fact that regular events are easier to report more accurately. Other studies have found different results. For example, Burton & Blair, 1991, using a similar response strategy elicitation method, find that accuracy improves with ‘recall and count’ for ATM transactions. But even here the effect of the reporting strategy on accuracy cannot be disentangled from the nature of the activity reported (i.e. people with fewer ATM transaction were using ‘recall and count’ strategies).

This discussion refers to studies looking at response strategies for frequency reporting where ‘specific’ periods are concerned. Overall, the ‘usual’ period is expected to evoke ‘rate based’ responses due to the general nature of the question in comparison to the ‘specific’ period (Angrisani et al., 2015). Edgar, 2009, looks at how response strategies regarding routine spending habits can change for ‘usual’ periods. The study, also uses a direct response strategy elicitation, and finds that response strategies on ‘usual’ period questions do not follow similar patterns to response strategies on ‘specific’ period questions. More specifically, Edgar, 2009 finds that responses to ‘usual’ periods about levels of expenditures usually follow some ‘rate based’ estimates and to a lesser extent estimates that are based on other type of simplification strategies such as budget calculations, guesses, single event retrievals and general impression. No work was done however to understand what induces these different response strategies.

Apart from the Edgar, 2009, study response strategies for expenditure reporting have been studied much less than those for frequency reporting. Although it is often assumed that they have many similarities as usually the latter is based on the former (Edgar, 2009), very few studies have compared the two of them. Beegle et al., 2012, conclude that the two processes are different as they discover different results in the comparison of reported expenditure levels than in the comparison of reported expenditure frequency. In contrary to results concerning expenditure levels, the median and the average number of reported payments were higher in ‘usual’ recall periods than in ‘specific’ ones (Beegle et al., 2012).

This study looks at both refill frequency and expenditure level reporting to test if some of the findings regarding frequency reporting, also apply in the realm of expenditure level reporting.

3. Data and methodology

3.1 Case study

The study took place in the semi-urban community of Bambadinca situated in the Bafatá region of the Northeast part of Guinea-Bissau (see Chapter 1 & Chapter 3). Payment data was extracted from clients of a solar hybrid mini-grid operating in the community since November 2014 (see Chapter 3 for a description).

3.2 Actual expenditure data

The payment system for the clients of the mini-grid is based on prepaid meters that clients must refill every time they run out of credit. Credit is purchased in the mini-grid station. Clients have top-up cards which are updated in relation to the amount purchased each time. These cards are subsequently used to update the meter at home. A comprehensive database regarding the time, date and size of these top-ups was made available to us by SCEB. This constitutes our actual expenditure dataset⁴⁰.

3.3 Expenditure survey

We designed a household survey containing a series of questions on the level of energy expenditures and frequency of payments. A random design was used. The randomization was undertaken at the household level. Half of the respondents were asked to state how much they paid to buy electricity and how many times they went to buy refills 'last week' (the question was phrased the 'previous seven days' to avoid confusion about what constitutes the 'last week'). This was the 'specific' period (see Fig.1).

⁴⁰ There have been some errors in this database, due to some technical problems related to card refill and the updating of meters. However, the database has been monitored closely and corrected by the SCEB personnel and therefore it is assumed that these errors are negligible.

How much did you spend in the previous seven days (last week) for credit refills for your electricity meter?	Last week Other _____
How many times did you go the previous seven days (last week) to buy these credit refills?	Last week Other _____

Fig 1: 'Specific period'

The other half of respondents were asked to state how much they paid to buy electricity and how many times they went to buy refills per week (referring to a normal generic week). This was the 'usual' period (see Fig.2)

How much do you spend per week normally for credit refills for your electricity meter?	Per week Other _____
How many times per week do you normally go to buy these credit refills?	Per week Other _____

Fig. 2: 'Usual' period

Although questions were asked on a weekly basis, respondents were permitted to answer for another period if they preferred, allowing us to capture more successfully the more infrequent payments. Information on relevant socio-economic characteristics was also collected along with information on household energy decision making, purchase habits and satisfaction with the service. The full survey can be found in the Appendix.

The survey was implemented in two waves. The first wave took place between the 7th and 26th of November 2015. The population of interest are households who receive electricity from the Community Energy Service of Bambadinca. At the time of this first survey, SCEB had 373 clients in total: 271 were households, 93 businesses and 11 institutions. All household clients of the service at the time were contacted and overall 241 household clients participated. Of these, 12 observations had to be dropped as we were not able to identify the client in the SCEB client expenditure database. This was because some clients shared the same name and could not be distinguished. An additional 9 clients were dropped because there was not enough information in the database. This was either because clients reported to have not used the service for a while or because they had just started using the service. An additional 28 clients were interviewed in the second wave of the survey, between 2nd and 5th of May 2016. In all

cases, the person who makes the decision regarding meter top-ups was interviewed. If they were not available another member of the household was interviewed who was knowledgeable on the household's energy expenditures.

The survey was originally written in Portuguese and the enumerator translated orally the questions from Portuguese to the local Creole dialect. Each survey took on average 10 minutes to complete.

3.4 Modelling framework

Three measures for reported accuracy were constructed, drawing from common practices in literature (Koijen et al., 2013; Kreiner et al., 2013; Menon, 1993).

The first measure of accuracy looks at *correlations* between reported and actual levels of expenditure and refill frequencies. The following OLS models are estimated (these models are tested separately for the 'usual' and the 'specific' period):

$$\begin{aligned} Y_{jactualexpenditure} &= a + \beta X_{jreportedexpenditure} + \varepsilon_j \\ Y_{jactualrefillfrequency} &= a + \beta X_{jreportedrefillfrequency} + \varepsilon_j \end{aligned}$$

Where $Y_{jactualexpenditure}$ is the real level of expenditure and $X_{jreportedexpenditure}$ is the reported expenditure in the survey, and $Y_{jactualrefillfrequency}$ is the real level of refill frequency and $X_{jreportedrefillfrequency}$ is the refill frequency reported in the survey.

The second measure looks at *absolute total differences* between reported spending in the survey and actual expenditures. For the 'specific' period this refers to the absolute difference between survey reporting and actual expenditures last week, and for the 'usual' period this refers to the absolute difference between survey reporting and average weekly expenditures in the previous month. The third measure looks at the *absolute relative differences* between reported spending and actual expenditures (reported spending minus actual expenditure divided by actual expenditures), reported as percentages. These last two measures will be referred to as *total* and *relative measurement errors*. Usually one of the two measures is reported in similar studies (Koijen et al., 2013; Kreiner et al., 2013; Menon, 1993). The same measures are also constructed for the case of frequency of refills.

The random assignment of the two alternative recall periods allows us to study the effect they each have on accuracy i.e. on the total and relative measurement errors. Random

assignment, at least in theory, means that relevant respondent and household characteristics, both unobserved and observable, are orthogonal to the causal mechanism of interest.

Therefore, to estimate the average effects on measurement error of the two different periods (i.e. the ‘specific’ and the ‘usual’ periods), the following Ordinary Least Squares (OLS) models are estimated:

$$Y_{j\text{absoluteerrorexpenditure}} = a + \beta_p \text{UsualPeriod}_j + \beta_x X_j + \varepsilon_j$$

$$Y_{j\text{absoluteerrorrefills}} = a + \beta_p \text{UsualPeriod}_j + \beta_x X_j + \varepsilon_j$$

$$Y_{j\text{relativeerrorexpendture}} = a + \beta_p \text{UsualPeriod}_j + \beta_x X_j + \varepsilon_j$$

$$Y_{j\text{relativeerrorrefills}} = a + \beta_p \text{UsualPeriod}_j + \beta_x X_j + \varepsilon_j$$

Where Y_j represents the various measurement errors considered (total and relative, for expenditure levels and for refill frequency), $\text{UsualPeriod}_j = 1$ when respondent is asked to report on the ‘usual’ period and $\text{UsualPeriod}_j = 0$ when respondent is asked to report on the ‘specific’ period. Therefore β_p measures the average effect on accuracy between the two different periods. $\beta_x X_j$ are additional controls on observable characteristics, and ε_j is an error term.

One of these controls is a measure of irregularity. We use as a measure of the irregularity of weekly refill frequency the standard deviation for weekly refill rate last month. To be able to make comparisons across different expenditure levels and refill frequency levels for this measure of irregularity we divided the standard deviations with the mean. To assess the role of reporting strategy on accuracy this measure of irregularity is interacted with UsualPeriod_j . The coefficient of this interaction is the effect of the ‘rate based’ response strategy on accuracy in comparison to the ‘recall and count’ response strategy.

4. Results

4.1 Summary statistics

4.1.1 Sample characteristics

Tables 1, 2 and 3 present the relevant sample characteristics on demographics and energy use patterns, habits and attitudes for the whole sample and for the sub-samples answering the ‘specific’ and the ‘usual’ period questions. In addition, the randomization procedure is validated through an estimation of differences between the means of the different sub-samples (last column in each table). Overall, there are no observable significant differences in any of the relevant characteristics.

Table 1 presents the demographics of the sample⁴¹. Around 45% of respondents are female. The average age of respondents is approximately 35 years and the average household size is 13. Just under 20% of respondents have had no education, 31% had only primary school education, 41% had secondary education and only 8% had some university education. As far as household income level is concerned, due to high income variability and the absence of stable sources of income for most of Bambadinca’s households, we had to resort to a direct subjective assessment of household income. The enumerator, who had local knowledge, was asked to choose between four different levels of income classification for each household, following the conclusion of each interview: ‘high income’, ‘medium income’, ‘poor’ and ‘very poor’. Subsequently, roughly 19% of households were classified as ‘high income’, 49% as ‘medium income’ and 32% as ‘poor’. None of the households was classified as ‘very poor’ reflecting the fact that households from the lowest income group in Bambadinca had not made an electricity connection at the time of the survey.

⁴¹ The sample is not representative of the Bambadinca population, as only households using the electricity service (the target population) were interviewed. But it is representative of the clients of the electricity service, since a large proportion of the population was interviewed.

TABLE 1 SUMMARY STATISTICS AND VALIDATION OF RANDOMIZATION FOR RESPONDENT AND HOUSEHOLD CHARACTERISTICS

	Whole sample	Specific period 'Last Week'	Usual period 'Per Week'	P-value
Number of observations	248	126	122	
Respondent is female (%)	44.94	44	45.90	0.77
Average age of respondent (years)	35.43	35.45	35.41	0.98
Average household size	13.08	12.99	13.18	0.85
Respondent never had any schooling (%)	19.76	19.84	19.67	0.97
Respondent received primary education (%)	31.05	27.78	34.43	0.26
Respondent received secondary education (%)	41.13	44.44	37.70	0.28
Respondent received university education (%)	8.07	7.94	8.2	0.94
High income household (%)	19.35	18.25	20.49	0.66
Medium income household (%)	48.79	49.21	48.36	0.89
Poor household (%)	31.85	32.54	31.15	0.81
Very poor household (%)	0	0	0	

The table validates that the two groups in the survey are balanced across respondent and household characteristics. The p-values are derived from t-tests.

Table 2 reports households' energy using habits and experience with the service. The great majority of households (94%) have had their meters installed for at least three months at the time of the survey. Around a third of respondents do not participate in decision making regarding energy use, 13% decide jointly with someone else, and 54% are the sole decision makers. In terms of purchasing credit for the meter the role is reversed as only 21% of respondents reported always going in person to buy more credit, with 17% reporting that they only buy credit in person sometimes. The remaining 62% never buys credit in person. Finally, overall reported satisfaction with the service is relatively high with 2.01 average on a five-point scale (1 being very satisfied and 5 very dissatisfied).

TABLE 2 SUMMARY STATISTICS AND VALIDATION OF RANDOMIZATION FOR ENERGY USING PATTERNS AND ATTITUDE TOWARDS THE SERVICE

	Whole sample	Specific period 'Last Week'	Usual period 'Per Week'	P-value
Respondent is a decision maker for energy (%)	53.63	52.38	54.92	0.69
Respondent is a partial decision maker for energy (%)	12.90	12.7	13.11	0.92
Respondent is not a decision maker for energy (%)	33.47	34.92	31.97	0.62
Respondent always recharges himself (%)	20.56	19.84	21.31	0.78
Respondent sometimes recharges himself (%)	17.34	19.84	14.75	0.29
Respondent never recharges himself (%)	62.1	60.32	63.93	0.56
Meter has been installed in the household for at least 3months (%)	93.55	93.65	93.44	0.95
Meter has been installed in the household for 2 months only (%)	3.23	3.97	2.46	0.5
Meter has been installed in the household for 1 month only (%)	3.23	2.38	4.1	0.45
Average level of dissatisfaction with service (5-point scale 1= very satisfied, 5=very dissatisfied)	2.01	1.95	2.07	0.25

The table validates that the two groups in the survey are balanced across energy using habits and attitude towards the service. The p-values are derived from t-tests.

Table 3 reports the characteristics of energy expenditures. Results show that the week before they were surveyed households spent on average 2733 FCFA to refill their meters and went on average 1.99 times to buy this credit. The average weekly expenditure in the last month was lower however (2362 FCFA), and so was the average weekly refill frequency (1.83).

TABLE 3 SUMMARY STATISTICS AND VALIDATION OF RANDOMIZATION FOR ENERGY EXPENDITURE

	Whole sample	Specific period 'Last Week'	Usual period 'Per Week'	P-value
Average expenditure last week (FCFA)	2733	2770	2694	0.84
Average refill frequency last week	1.99	2.01	1.97	0.86
Average weekly expenditure last month (FCFA)	2362	2318	2408	0.78
Average weekly refill frequency last month	1.83	1.83	1.82	0.95
Average irregularity of weekly refill frequency last month	0.48	0.48	0.47	0.83

The table validates that the two groups in the survey are balanced across energy expenditures. The p-values are derived from t-tests. The irregularity measure is the standard deviation divided with the mean.

4.1.2 Reported expenditure

Table 4 reports summary statistics for the reported expenditure, broken down by sub-sample. As can be seen for both elicitation frameworks, reported spending is higher than the actual spending reported in Table 3. This demonstrates that there is a general tendency to over-report energy expenditures in the survey regardless of the elicitation method that is being used. Both the mean and the median as well as the standard deviation of reported expenditure is lower when elicited with the ‘specific’ as opposed to when elicited with the ‘usual’ period. A similar relationship holds for the reporting on average weekly refill frequency, although in this case the median of the two measures is equal. These findings are contrary to expectations from the literature, which finds that ‘specific’ periods elicit higher and more variable measures (Angrisani, Kapteyn, & Schuh, 2015; Beegle et al., 2012).

TABLE 4 SUMMARY STATISTICS OF REPORTED EXPENDITURE

Reported average weekly/last week expenditure (FCFA)	Reported average weekly/last week expenditure (FCFA)		Reported average refill frequency per week/last week	
	Specific period 'Last Week'	Usual period 'Per Week'	Specific period 'Last Week'	Usual period 'Per Week'
Mean	3434	4271	2.28	2.74
Median	2340	2800	2	2
Standard deviation	3015	4547	1.95	2.86

4.1.3 Measures of response accuracy

The summary statistics of the total and relative measurement errors, are reported in Table 5. Total measurement errors are smaller in the case of the ‘specific’ period than in the case of the ‘usual’ period as far as the mean and their median are concerned. This difference of the means is also statistically significant. This holds in both cases of reported levels of expenditure and refill frequency. Similar patterns hold for the relative measurement errors (Table 6).

This suggests therefore that the ‘specific’ period gives significantly more accurate results. This is in line with other findings in literature (Beegle et al., 2012). The lower mean results of the ‘specific’ period found in this study contrary to expectations, is due to the fact

that there is an over-reporting of expenditure. This signifies the more accurate the measure, the lower the means.

It is also interesting to note that in reported spending, in the ‘specific’ period more than 25% of responses were fully accurate (i.e. zero measurement error); this goes to over 50% for the case of reported refill frequency. In contrast in the ‘usual’ period this figure drops to 1% and 5% respectively.

TABLE 5 MEASURES OF DISPERSION OF TOTAL ERROR IN LEVEL OF EXPENDITURE AND REFILL FREQUENCY REPORTING

	<i>Total expenditure error</i>			<i>Total refill frequency error</i>		
	Specific period ‘Last Week’	Usual period ‘Per Week’	P-value	Specific period ‘Last Week’	Usual period ‘Per Week’	P-value
Mean	1023.59	2018.39	0.0008	Mean	0.56	1.18
Median	500	1030		Median	0	0.6
Standard deviation	1838.63	2617.27		Standard deviation	0.96	1.54
Percentiles				Percentiles		
1%	0	0		1%	0	0
5%	0	60		5%	0	0
10%	0	160		10%	0	0.1
25%	0	360		25%	0	0.2
50%	500	1030		50%	0	0.6
75%	1000	2530		75%	1	1.5
90%	2500	5440		90%	2	3.8
95%	4000	7900		95%	2.4	4.8
99%	8000	11170		99%	4	6.5

Total expenditure error: Absolute total differences between reported spending and actual expenditure last week or per week;
 Total refill frequency error: Absolute total differences between reported refill frequency and actual refill frequency last week or per week. The p-values are derived from t-tests.

TABLE 6 MEASURES OF DISPERSION OF RELATIVE ERROR IN LEVEL OF EXPENDITURE AND REFILL FREQUENCY REPORTING

	<i>Relative expenditure error</i>			<i>Relative refill frequency error</i>		
	Specific period 'Last Week'	Usual period 'Per Week'	P-value	Specific period 'Last Week'	Usual period 'Per Week'	P-value
Mean	78.94	161.15	0.05	Mean	47.31	106.73
Median	20	52.51		Median	0	42.857
Standard deviation	259.34	288.54		Standard deviation	118.94	191.58
Percentiles				Percentiles		
1%	0	0		1%	0	0
5%	0	5.41		5%	0	0
10%	0	9.38		10%	0	4.76
25%	0	22.73		25%	0	16.67
50%	20	52.51		50%	0	42.86
75%	52.05	157.35		75%	40	100
90%	133.33	400		90%	100	268.42
95%	354.55	681.25		95%	233.33	525
99%	1150	1328.57		99%	600	900

Relative expenditure error: absolute relative differences between reported spending and actual expenditure last week or per week (reported in percentages); Relative refill frequency error: Absolute relative differences between reported refill frequency and actual refill frequency last week or per week (reported in percentages). The p-values are derived from t-tests.

4.2 Results

4.2.1 Correlations

Table 7 reports the results of an Ordinary Least Squares Regression (OLS) of survey reported expenditures to actual expenditures, broken down by the the different elicitation periods, in order to see how satisfactorily survey responses, predict real expenditures.

Overall, in all cases there are important individual-level deviations between the survey reported and the actual expenditures and refill frequencies. The ‘specific’ period predicts expenditures last week with a significant slope of 0.60 and an adjusted R-squared of 0.57 (this means that only 57% of the variation is explained by the survey responses). The results are better in the case of predicting refill frequency. With a significant slope of 0.69, and an adjusted R-squared of 0.7.

The ‘usual’ period predicts average weekly expenditures last month with a significant slope of 0.51 and an adjusted R-squared of 0.67. Interestingly, although the ‘specific’ period fares better in terms of the size of the prediction, it seems to be capturing less of the variation than the ‘usual’ period. This discrepancy does not hold with predictions of refill frequency as both the slope (0.53) and R-squared (0.66) are lower in the ‘usual’ than in the ‘specific’ period.

Overall, it appears that both periods predict refill frequency better than expenditure levels.

TABLE 7 CORRELATION OF SURVEY REPORTED EXPENDITURE AND FREQUENCY OF REFILLS WITH ACTUAL EXPENDITURE AND FREQUENCY OF REFILLS

	Expenditure last week	Expenditure per week last month	Frequency of refills last week	Frequency of refills per week last month
Constant	627.24* (331.76)	236.76 (244.36)	0.41*** (0.12)	0.39*** (0.13)
Survey reported weekly expenditure (Specific period)	0.60*** (0.12)		0.69*** (0.07)	
Survey reported weekly expenditure (Usual period)		0.51*** (0.07)		0.53*** (0.06)
<i>Adj R-squared</i>	0.57	0.67	0.7	0.66
<i>Number of observations</i>	117	121	114	119

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported).

4.2.2 Reporting period effects on total and relative measurement errors

The following regressions are looking at the effect of the different recall periods, as well as of other determinants, on the level of error in expenditure level and refill frequency reporting. As mentioned previously both total and relative measurement errors have been used as measures of accuracy in the literature of survey methodology. Accuracy measures based on total differences, overemphasize deviations on higher expenditure levels, while relative measures overemphasize deviations on smaller expenditure levels. For that reason, average weekly expenditure last month and average weekly refill frequency the month prior to the survey, were also added as controls in the regressions. A table with an explanation of all variable names used in the regressions can be found in the Appendix.

Table 8 explores the determinants of the total level of measurement error. The ‘usual’ week elicitation has a positive and significant effect on the level of error on both expenditure level and refill frequency reporting. When controlling for covariates, the effect of the ‘usual’ week remains strong for all extended models. This finding provides further confirmation that the ‘usual’ period recall gives less accurate results.

As far as the effect of other covariates on total measurement error are concerned, the average weekly expenditure (or average weekly refill frequency), the irregularity of weekly refill frequency and level of dissatisfaction with the service, are the only measures that retain a strong effect in all the extended models.

The average level of weekly expenditure (or weekly refill frequency) and irregularity of weekly refill frequency, as expected, have a significant and positive effect on total measurement error. This is in line to Menon, 1993 findings regarding the negative effect of irregularity of events on accuracy of frequency reporting. The level of dissatisfaction with the service has a positive effect on total measurement error, which indicates that over-reporting could be partly an outcome of protest for the service charges.

Socio-economic variables like household size, gender of respondent, household income level, age of respondent and in which of the two survey waves the surveyed household participated are only robust in some of the models. In addition, the regression controls for other respondent characteristic expected to affect performance in survey responses namely the level of schooling of respondent, the time the meter has been used for, if respondent actively takes part in decision making about energy and if respondent purchases the refills in person. As none of these variables were significant in any of the models their coefficients are not reported.

These findings indicate that misreporting is largely linked to expenditure levels and refill frequency patterns and less due to respondent characteristics. This is not in agreement to other studies measuring the effect of different aspect of expenditure survey design on survey responses, which have found respondent specific characteristic to have an effect (Beegle et al., 2012; Comerford et al., 2009; Winter, 2004).

The interaction of irregularity of weekly refill frequency with the ‘usual’ period has a negative effect on error. In other words, as irregularity of weekly refill frequency increases the measurement error for the ‘specific’ period in comparison to the ‘usual’ period increases. However, this effect is only significant for the error in refill frequency reporting, when controlling for average weekly refill frequency last month, and not for the error in expenditure level reporting.

TABLE 8 DETERMINANTS OF TOTAL LEVEL OF MEASUREMENT ERROR ON EXPENDITURE AND REFILL FREQUENCY REPORTING

	Total expenditure level error	Total expenditure level error extended model	Total expenditure level error extended model controlling for spending level	Total refill frequency	Total refill frequency extended model	Total refill frequency extended model controlling for refill frequency level
Constant	1023.59*** (169.97)	-1661.57 (1012.47)	-1268.7 (961.62)	0.56*** (0.09)	-1.43*** (0.51)	-1.22** (0.50)
Usual period	994.81*** (292.42)	1068.03*** (405.17)	1131.87*** (383.04)	0.61*** (0.17)	0.64*** (0.23)	0.77*** (0.21)
Household size		38.85** (19.09)	30.64 (19.52)		0.03* (0.02)	0.02 (0.02)
High income		1642.7*** (542.08)	1238.59** (604.54)		0.61* (0.31)	0.40 (0.30)
Female		629.81 (437.98)	389.30 (424.38)		0.57** (0.23)	0.34 (0.23)
Age		-23.54* (13.40)	-21.62 (13.86)		-0.006 (0.006)	-0.004 (0.006)
Irregularity		1529.68*** (504.30)	1387.11*** (528.82)		0.46** (0.18)	0.41** (0.19)
Irregularity*Usual period		-662.18 (794.74)	-819.8 (727.71)		-0.29 (0.37)	-0.57* (0.32)
Average weekly expenditure			0.18** (0.08)			
Average weekly refill frequency						0.20*** (0.06)
Level of dissatisfaction		468.44** (185.54)	389.69** (184.18)		0.30** (0.12)	0.22* (0.13)
Second survey wave		1531.72** (732.85)	1426.51** (705.85)		0.42 (0.27)	0.37 (0.28)
Number of observations	238	232	232	233	227	227
Adj R-squared	0.04	0.18	0.21	0.05	0.13	0.18

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Irregularity *Usual period: interaction between irregularity of weekly refill frequency and 'usual' period. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported). All regressions include additional controls regarding decision making on energy, refill habits, schooling levels, whether the household has the meter for at least three months and if the household belongs to the medium income level.

Table 9 presents the determinants of relative measurement errors. There is similarity to findings on total measurement errors as the ‘usual’ period has a positive effect on the relative measurement error of expenditure level and refill frequency reporting, which remains robust in all extended models. As expected, the level of average weekly expenditure (or weekly refill frequency) in this case has a negative significant effect on level of error. Here the interaction of the ‘usual’ period with irregularity of weekly refill frequency is significant and negative in all refill frequency error models and for the extended model of expenditure level error with spending level controls. Dissatisfaction significantly drives the results only for refill frequency error, in all cases. Finally, the socio-economic variables that were significant in some of the models in Table 8 loose their significance here, which further indicates that the measurement error is not driven by socio-economic factors.

Overall, the negative effect that irregularity of weekly refill frequency has through the ‘specific’ period indicates a negative effect of ‘recall and count’ strategies on accuracy for refill frequency reporting. This in contrary to Menon, 1993 findings that ‘rate based’ estimates give more accurate results, but in line with Burton and Blaire, 1991 who find that ‘rate based’ estimates give more accurate results. The fact that this finding is robust for fewer models of expenditure level error in comparison to the models of refill frequency error, indicates that the findings regarding frequency reporting (Menon, 1993) do not fully translate to expenditure level reporting. However, overall results regarding the effect of the different recall periods, the effect of other covariates and the correlations of real and reported measures show that these two process are largely linked.⁴²

⁴² We also tested the effect of two additional measures of irregularity concerning the expenditure levels. One is the irregularity of the amount purchased to refill the prepaid meters for which we calculated the standard deviation of refill amounts last month. The second one is irregularity of the weekly expenditure level, for which we calculated the standard deviation for average weekly expenditure last month. To be able to make comparisons across different expenditures and refill frequency levels, the standard deviations were divided with the respective means of the two measures. The first measure was added as a measure of similarity and the second as an additional measure of irregularity for the expenditure levels. Although it was assumed that the effect of similarity is negligible in this case study (as the refill process is very similar each time), the irregularity of the level of refill amounts could be capturing a similarity effect for expenditure level reporting. These measures of irregularity were not found to have any significant effect in none of the models above. Their effect was tested separately to avoid issues of multicollinearity. These results are therefore not reported here, but are available upon request.

TABLE 9 DETERMINANTS OF RELATIVE LEVEL OF MEASUREMENT ERROR ON EXPENDITURE AND REFILL FREQUENCY REPORTING

	Relative expenditure level error	Relative expenditure level error extended model	Relative expenditure level error extended model controlling for spending level	Relative refill frequency error	Relative refill frequency error extended model	Relative refill frequency error extended model controlling for refill frequency level
Constant	78.94*** (23.97)	29.73 (156.88)	-40.75 (149.42)	47.31*** (11.14)	-82.77 (78.72)	-106.39 (79.52)
Usual period	82.22** (35.54)	158.81*** (59.77)	147.35** (57.89)	59.42*** (20.80)	133.80*** (37.24)	118.69*** (33.52)
Household size		2.35 (2.54)	3.82 (2.49)		1.82 (1.69)	2.63 (1.69)
High income		17.28 (68.12)	89.77 (71.29)		-4.96 (30.96)	18.43 (29.67)
Female		-10.95 (57.53)	32.20 (52.45)		41.10 (28.21)	66.75** (30.27)
Age		-1.86 (2.11)	-2.21 (2.09)		-0.08 (0.70)	-0.28 (0.67)
Irregularity		143.86 (96.65)	169.44* (99.10)		79.92** (35.11)	85.29** (36.28)
Irregularity *Usual period		-220.69* (122.19)	-192.41* (116.28)		-182.27*** (60.55)	-151.77*** (52.39)
Average weekly expenditure			-0.03*** (0.008)			
Average weekly refill frequency						-22.97*** (6.77)
Level of dissatisfaction		37.57 (35.41)	51.69 (35.31)		32.53** (21.53)	41.29* (22.36)
Second survey wave		163.96 (106.95)	182.83* (106.19)		36.08 (43.13)	42.57 (41.06)
Number of observations	238	232	232	233	227	227
Adj R-squared	0.02	0.05	0.12	0.03	0.08	0.13

*p-value<0.1 **p-value<0.05 ***p-value<0.01. Irregularity *Usual period: interaction between irregularity of weekly refill frequency and 'usual' period. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported). All regressions include additional controls regarding decision making on energy, refill habits, schooling levels, whether the household has the meter for at least three months and if household belongs to the medium income levels.

4.2.3 Limitations and the use of the effects of cognitive difficulty as a robustness check

The main limitation of this study is that, our conclusions regarding the accuracy of the different response strategies are based on certain assumptions about how irregularity, and the nature of recall period affect the response strategies. These assumptions are informed by findings from previous studies. We cannot rule out however that the effect of the interaction between irregularity and recall period is not driven by the different response strategies used but by some other dynamic that we are unaware of. In other words, irregularity could be affecting the accuracy of responses to the ‘specific’ period for some reason other to response strategy change.

Due to time constraints associated with the fieldwork, we do not elicit a response strategy separately for each respondent. This is done in a number of studies by asking respondents to explain the way they formed their responses (Burton & Blair, 1991; Menon, 1993; Edgar, 2009).

In this section we use an additional confirmation of the response strategy shift we assumed using the cognitive effort of respondents as a proxy. A number of studies associate ‘recall and count’ response strategies with a higher cognitive effort than ‘rate based’ response strategies (Menon, 1993; Tourangeau et al., 2000).

Table 10 reports the effects of the elicitation period on the level of difficulty in reporting expenditure levels and refill frequency as assessed by the interviewer in a five-point scale (with 5 signifying maximum difficulty). We find that the ‘specific’ period, which produces more accurate results as per discussion above, is associated with a higher level of response effort, i.e. a higher level of difficulty as expected.

TABLE 10 THE EFFECT OF RECALL PERIOD ON DIFFICULTY OF EXPENDITURE LEVEL AND REFILL FREQUENCY REPORTING

	Specific period ‘Last Week’	Usual period ‘Per Week’	P-value
Difficulty of reporting 1	2.56	2.19	0.005
Difficulty of reporting 2	2.62	2.22	0.005

Difficulty of reporting 1: Difficulty of reporting level of expenditure in a 5-point scale (1= no difficulty).

Difficulty of reporting 2: Difficulty of reporting refill frequency in a 5-point scale (1= no difficulty).

The table tests that the two groups in the survey are differ in terms of the difficulty in reporting.

The p-values are derived from t-tests.

The fact that response difficulty seems to be significantly higher in the ‘specific’ elicitation period, serves as tentative confirmation of our priors that the ‘specific’ period, evokes more ‘recall and count’ strategies, while ‘usual’ period invoke more ‘rate based’ estimation strategies. Table 11 demonstrates that as irregularity of the reported task (irregularity of weekly refill frequency) increases, response difficulty significantly increases only for the ‘specific’ period. This is an indication that increased irregularity leads to switches in reporting strategy for the ‘specific’ period, from ‘rate based’ estimates to ‘recall and count’ strategies that are more time consuming, as is found in other studies (Menon, 1993). This does not happen for the ‘usual’ period. Therefore, we can argue that this is additional evidence that the negative effect of irregularity on response accuracy for the ‘specific’ period found in Tables 8 and 9 is due to the use of ‘recall and count’ instead of ‘rate based’ strategies.

TABLE 11 THE EFFECT OF IRREGULARITY ON DIFFICULTY OF REPORTING

	(1)	(2)	(3)	(4)
Constant	2.20*** (0.21)	2.15*** (0.17)	2.34*** (0.17)	2.10*** (0.17)
Irregularity	0.78* (0.24)	0.06 (0.31)	0.53* (0.3)	0.22 (0.36)
<i>Adj R-squared</i>	0.08	-0.0003	0.03	-0.005
<i>Number of observations</i>	114	120	114	120

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported).

1. Difficulty of reporting level of expenditure in a 5-point scale (1= no difficulty) for specific period ‘Last Week’.
2. Difficulty of reporting level of expenditure in a 5-point scale (1= no difficulty) for usual period ‘Per Week’.
3. Difficulty of reporting refill frequency in a 5-point scale (1= no difficulty) for specific period ‘Last Week’.
4. Difficulty of reporting refill frequency in a 5-point scale (1= no difficulty) for usual period ‘Per Week’.

5. Conclusions

This study uses data on actual energy expenditure available from a solar hybrid mini-grid in rural Guinea-Bissau and compares it to reported expenditure obtained via a survey to test the accuracy of reported energy expenditure within surveys when using differently defined recall periods. Through a randomized design we isolate the effects on response accuracy of asking respondents to state their expenditure in a ‘specific’ (‘last week’) as opposed to a ‘usual’ (‘per week’) period. This is the first study to compare survey data with real data on recurring household expenditures in a developing country in order to validate the accuracy of survey responses. In addition, this study focuses on energy expenditure reporting which has been largely overlooked in the literature despite the fact that collecting accurate information of energy expenditure is crucial for successful policy and project design.

Overall, our results indicate important individual-level deviations between survey reported, and actual expenditures levels and frequency of refills in all cases. Regardless of the period used there is a general tendency to over-report energy expenditures which is more pronounced with the use of the ‘usual’ period. This demonstrates that survey elicited expenditure data should be treated with caution.

In addition, we find that responses are more accurate and less noisy when ‘specific’ periods are used. The fact that ‘usual’ period recall gives less accurate results seems to be in line with other findings in literature (Beegle et al., 2012). However, the expectation from this literature is that responses to the ‘specific’ period will have an overall higher means (less forgetfulness) and larger dispersion measures (higher volatility) (Angrisani et al., 2015) which is opposite to our findings. The lower means results of the ‘specific’ period in our case, is due to the fact that there is an over-reporting of expenditure therefore the lower means indicate more accurate responses. This over-reporting can be partially driven by a tendency of certain respondents to overstate their responses due to dissatisfaction with the service, which is positively and significantly correlated with the level of measurement error in most error models. The fact that some of our results were found to diverge from the findings of other studies confirms that the results are sensitive to good-specific characteristics (Deaton & Grosh, 2000).

Results also indicate that misreporting is largely linked to expenditure and refill frequency patterns and not to socio-economic characteristics of the respondent as found in other studies (Beegle et al., 2012; Comerford et al., 2009; Winter, 2004).

More specifically, the level of average weekly expenditure (or weekly refill frequency) and irregularity of weekly refill frequency significantly affects both the total and relative measurement error. This is close to Menon, 1993 study that finds a negative effect of irregularity of events on accuracy of frequency reporting. Importantly, results suggest that the irregularity of weekly refill frequency affects negatively reporting error in the ‘specific’ period rather than in the ‘usual’ period. However, the effect is robust for most models of error on refill frequency reporting but less so for error on expenditure level reporting.

This final finding offers some evidence regarding the effect of response strategies on response accuracy. The ‘usual’ period has been shown to induce respondents to follow ‘rate based’ estimation strategies and the ‘specific’ period to induce respondents to follow ‘recall and count’ strategies, specifically when irregularity of weekly refill frequency increases. Therefore, the negative effect that irregularity of weekly refill frequency has through the ‘specific’ period implies that ‘recall and count’ strategies have a negative effect on accuracy, particularly for frequency reporting.

Results also suggest that findings of frequency reporting (Menon, 1993) do not fully correspond to expenditure level reporting, but that there are many similarities.

We were not able to collect detailed information about the respondents’ response strategy after the expenditure elicitation, which would confirm that the ‘specific’ period is indeed inducing more ‘recall and count’ strategies especially as irregularity of weekly refill frequency increases. Nevertheless, we use difficulty in responding (as assessed by the interviewer in a five-point scale) as a measure of response strategy used. ‘Recall and count’ response strategies are expected to be more difficult to respond to, rather than the ‘rate based’ estimates. We find that the ‘specific’ period is significantly more difficult overall to respond to, and that difficulty increases significantly in irregularity of weekly refill frequency only within the ‘specific’ period. This then confirms our priors.

Our findings have implications for policy as they indicate that overall survey elicited energy expenditure data should be treated with caution. Issues linked to the reported activity (expenditure levels, irregularity of refill frequency) and attitudes of the surveyed population that can lead to misreporting of expenditure (e.g. dissatisfaction with the service) should be taken into consideration when interpreting survey elicited energy expenditure data. Finally, although we demonstrate that using the ‘specific’ period helps reduce measurement error to a certain extent, the variability of the reported measure should also be taken into consideration when choosing the appropriate ‘recall’ period.

The main limitation of this study is that we were not able to elicit response strategies separately, which would have provided additional evidence regarding the effect of response strategy on response accuracy. In addition, the limited sample size of this case study does not allow for a full exploration of the source of other potential biases in reporting, or to explore other effects of survey design. However, we are hoping to introduce a way in exploring expenditure reporting. Response strategy elicitation methods and (or) the use of larger sample sizes from clients of large utilities could be used in the future, to confirm the evidence presented by this study and also test other aspects of survey design and theories of response strategies and study their interaction. Such an exercise can also enhance our knowledge about potential sources of consumer misunderstanding of their energy expenditures.

6. References

Angrisani, M., Kapteyn, A., & Schuh, S. D. (2015). Measuring Household Spending and Payment Habits: the Role of Typical and Specific Time Frames in Survey Questions, in Christopher D. Carroll, Thomas F. Crossley, and John Sabelhaus, *Improving the Measurement of Consumer Expenditures. Studies in Income and Wealth, University of Chicago Press, 2015.*

Beegle, K., De Weerdt, J., Friedman, J., & Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania. *Journal of Development Economics, 98*(1), 3-18.

Blair, E., & Burton, S. (1987). Cognitive processes used by survey respondents to answer behavioral frequency questions. *Journal of Consumer Research, 14*(2), 280-288.

Browning, M., Crossley, T. F., & Weber, G. (2003). Asking consumption questions in general purpose surveys. *The Economic Journal, 113*(491), F540-F567.

Browning, M., Crossley, T. F., & Winter, J. (2014). The measurement of household consumption expenditures. *Annu. Rev. Econ., 6*(1), 475-501.

Brutscher, P.-B. (2011). Payment Matters? -An Exploratory Study into the Pre-Payment Electricity Metering.

Burton, S., & Blair, E. (1991). Task conditions, response formulation processes, and response accuracy for behavioral frequency questions in surveys. *Public Opinion Quarterly, 55*(1), 50-79.

Comerford, D., Delaney, L., & Harmon, C. (2009). Experimental tests of survey responses to expenditure questions. *Fiscal Studies, 30*(3-4), 419-433.

Congdon, W. J., Kling, J. R., & Mullainathan, S. (2011). *Policy and choice: Public finance through the lens of behavioral economics*: Brookings Institution Press.

Crossley, T., D'Ardenne, J., Blake, M., Oldfield, Z., Winter, J., & (2014). Testing Quick Expenditure Questions, in Understanding Society Innovation Panel Wave 6: Results from Methodological Experiments. *Understanding Society Working Paper Series, 2014-04.*

Deaton, A., & Grosh, M. (2000). Consumption. in Grosh, Margaret and Paul Glewwe, eds. *Designing Household Survey Questionnaires for Developing Countries: Lessons from 15 Years of the Living Standards Measurement Study*. Washington D.C.: World Bank.

Edgar, J. (2009). What does 'usual' usually mean? *Unpublished manuscript, Bur. Labor Stat., Washington, DC.*

Fairbrother, M. (2014). Assessing the Feasibility of More Precisely Measuring Household Energy Consumption in Understanding Society Innovation Panel Wave 6: Results from Methodological Experiments. *Understanding Society Working Paper Series, 2014-04.*

Jack, B. K., & Smith, G. (2016). Charging Ahead: Prepaid Electricity Metering in South Africa: National Bureau of Economic Research.

Kahneman, D. (2003). A perspective on judgment and choice: mapping bounded rationality. *American psychologist, 58*(9), 697.

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. *Heuristics and biases: The psychology of intuitive judgment, 49*, 49-81.

Koijen, R. S., Van Nieuwerburgh, S., & Vestman, R. (2013). Judging the Quality of Survey Data by Comparison with 'Truth' as Measured by Administrative Records: Evidence from Sweden. *Chapter in NBER Book Improving the Measurement of Consumer Expenditures, Christopher Carroll, Thomas Crossley, John Sabelhaus, eds., Forthcoming.*

Kreiner, C. T., Lassen, D. D., & Leth-Petersen, S. (2013). Measuring the accuracy of survey responses using administrative register data: evidence from Denmark: National Bureau of Economic Research.

Menon, G. (1993). The effects of accessibility of information in memory on judgments of behavioral frequencies. *Journal of Consumer Research, 20*(3), 431-440.

Menon, G., Raghbir, P., & Schwarz, N. (1995). Behavioral frequency judgments: An accessibility-diagnosticity framework. *Journal of Consumer Research*, 22(2), 212-228.

NSSO Expert Group. (2003). Suitability of Different Reference Periods for Measuring Household Consumption: Results of a Pilot Survey. *Economic and Political Weekly*, 37(4), 307-321.

Pudney, S. (2008). Heaping and leaping: Survey response behaviour and the dynamics of self-reported consumption expenditure. *ISER Working Paper Series 2008-09, Institute for Social and Economic Research, University of Essex*.

Qiu, Y., Xing, B., & Wang, Y. D. (2016). Prepaid electricity plan and electricity consumption behavior. *Contemporary Economic Policy*.

Schnell, R. (2013). Linking Surveys and Administrative Data; in: Engel, U., Jann, B., Lynn, P., Scherpenzeel, A., and Sturgis P. (Eds.): Improving Survey Methods: Lessons from Recent Research. *New York: Routledge, Taylor & Francis Group*, 273-287.

Tourangeau, R., Rips, L. J., & Rasinski, K. (2000). *The psychology of survey response*: Cambridge University Press.

Tversky, A., & Kahneman, D. (1975). Judgment under uncertainty: Heuristics and biases *Utility, probability, and human decision making* (pp. 141-162): Springer.

Winter, J. (2004). Response bias in survey-based measures of household consumption. *Economics Bulletin*, 3(9), 1-12.

7. Appendix

7.1 Explanation of variable names used in regressions

	Definition
Usual period	Dummy; 1= respondent respond to the 'usual' period
Household size	Household size
High income	Dummy; 1=household belongs to the highest oncome category
Female	Dummy; 1= respondent is Female
Age	Age of respondent (in years)
Irregularity	Irregularity of weekly refill frequency
Irregularity*Usual period	Irregularity of weekly refill frequency *Usual period
Average weekly expenditure	Average weekly expenditure last month
Average weekly refill frequency	Average weekly refill frequency last month
Level of dissatisfaction	Level of dissatisfaction with service on a 5-point scale (1= very satisfied)
Second survey wave	Dummy; 1=household was interviewed in the second survey wave

7.2 Survey draft

Note to interviewer:

Ask: "Who makes the decisions regarding the electricity in this household? Can I talk to this person?". If not available ask: "When can I come back to talk to that person?".

If you can not talk to this person (especially if the person does not want to be interviewed) or if anyone else in this family prefers to answer this questionnaire, try to insist on the correct person answering, explaining that the participation of the correct person in this questionnaire is very important to us to obtain the right information.

The last resort is to agree to talk to someone instead who is well informed of the daily activities of the household and who is an important part in the decision making process of the household.

After you have established who to talk to, communicate the following information:

We are conducting a survey in your community that is part of a research initiative carried out by a PhD student at the London School of Economics and Political Science, a university in London. This is in partnership with 'TESE' an NGO working in Guinea-Bissau on infrastructural projects, including energy. The purpose of the questionnaire is to study the energy community service of Bambadinca.

These questions should take around 10 minutes to complete.

Your answers will be strictly confidential and will not be shared with anyone else. Answers will only be used anonymously for research purposes.

Participation is voluntary and you can refuse to participate without providing an explanation and without any consequences. If you agree to participate in the survey you have the right to stop whenever you want.

Your participation is very important to us. We will use the information that you and other families give us to understand more fully the factors affecting the success of the community energy project. This is in the advancement of academic knowledge and this knowledge could serve future energy policies in Guinea-Bissau.

Do you have any questions? **May I continue interviewing you?**

Your responses will have no influence over the way the energy service is offered to you (tariffs etc.) It is very important that you give honest answers and not over or understate the answers. This is because if the information we collect is not true, the outputs of the survey will not be beneficial to your community or Guinea-Bissau.

Client number	
Client name	
Name of respondent	
<u>Note to interviewer:</u> are you speaking with the person who makes the financial decisions and decisions regarding the purchase of energy products in this household?	Yes No Other. Specify_____
What is the gender of the respondent?	Female Male
What is their age? (<u>Note to interviewer:</u> If they don't know their age or if they seem to be giving you the wrong answer take a note of the age they seem to have. As an indication ask them what is the age of their eldest son)	
What is your education level?	No schooling Primary schooling Secondary schooling Superior schooling Other. Specify_____
What is your relationship to the head of the household?	
How many people live in this household including yourself? By household I mean all individuals who normally live and eat their meals together in this household and share the expenses. (<u>Note to interviewer:</u> Here, to make sure you obtain the right response, make sure to have a short conversation about what the relationship of each member is to the respondent. Example: Begin by asking who else lives here)	
What is the ethnicity of the household?	Fula Mandinga Balanta Beafada Papel Cabo-verdiana

	Other. Specify _____
Which family member goes to buy credit refills for electricity?	
Which family member decides the level of credit refills for electricity?	

Randomized elicitation period:

1. Specific period

How much did you spend last week for credit refills for your electricity meter?	Per week Other _____
How many times did you go last week to buy these credit refills?	Per week Other _____

2. ‘Usual’ period

How much do you spend normally per week for credit refills for your electricity meter?	Per week Other _____
How many times do you normally go per week to buy these credit refills?	Per week Other _____

Additional Questions about the service:

How satisfied are you with the service?	Very satisfied Satisfied Not satisfied nor dissatisfied Dissatisfied Very dissatisfied
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Questions for the interviewer:

what is the income level of this household in your opinion?	High income Medium income Poor Very poor
Rate the interviewer's effort to answer the question on expenditures in terms of time spent? (with 1 expressing the least possible effort)	1 2 3 4 5
Rate the interviewer's effort to answer the question on the frequency of credit refills in terms of time spent? (with 1 expressing the least possible effort)	1 2 3 4 5
Did someone else respond for them?	Yes No Other _____

Chapter 5

The determinants of expenditure patterns for prepaid electricity: evidence from a solar hybrid mini-grid in Guinea-Bissau

Abstract

This study looks at prepayment patterns for electricity services, offered by a solar hybrid mini-grid in rural Guinea-Bissau, and how they are affected by a number of socio-economic factors, the equipment in use, self-control problems, social pressures to share money and other intra-household dynamics as well as being charged a time-varying tariff. Understanding these dynamics is important in order to identify the advantages and limitations of the prepayment method in comparison to traditional monthly billing methods. Findings indicate that prepayment helps address both income constraints as well as self-control problems. Overall, there is a preference for small and frequent repayments. The level of monthly expenditure is driven positively, amongst other factors, by income levels and using the service for income generating activities. Self-control problems affect negatively the level of refill amounts indicating that customers with self-control problems use smaller refill amounts as a method to commit to using less electricity at home. Similarly, individuals charged a higher tariff for their consumption between 7pm to 12am choose smaller refill amounts possibly as a method to control their consumption patterns. These findings are important for policy. Namely results advise against the use of a minimum refill amount and in favour of putting in place schemes that will encourage income generating activities at the household level (e.g. credit and rental schemes for appliances).

1. Introduction

One of the main challenges facing electricity access policies in developing countries is ensuring that the new clients, who in these contexts often face severe income and liquidity constraints, are able to pay the bills associated with the electrification services (Jack & Smith, 2015). Inability to pay can lead to non-payment, which negatively impacts utility revenues and investments in infrastructure to expand access to electricity, but also the quality of the electricity provided (McRae, 2014; Szabó & Ujhelyi, 2014). Prepaid meters are seen as a promising technological solution to limit non-payment linked to traditional billing methods (Jack & Smith, 2016), and help customers to manage their electricity consumption (Darby, 2012). As prepaid meters offer flexibility in the payment regime and allow consumers to link their consumption with their expenditure they are expected to help address a number of issues. These can be income and liquidity constraints or non-income factors like self-control problems, intra-household pressures and inability to understand traditional billing methods (Jack & Smith, 2015; Jack & Smith, 2016). However, little research has been done to see how these factors actually affect prepayment patterns. Such an exercise is warranted to confirm the relative strengths and weaknesses of the prepayment method, inform the design of prepayment schemes and also shed light on the underlying limitations of traditional billing methods.

Prepaid meters is a payment method for electricity that has been used in a number of developed (Australia, Great Britain, Northern Ireland, North America) (Boardman & Fawcett, 2002; Brutscher, 2011, 2012b; Qiu, Xing, & Wang, 2016; Sharam & Energy Action, 2003) and developing countries and it is expected to expand quickly in the coming years (e.g. South Africa and other projects in Sub-Saharan Africa) (Jack & Smith, 2015). In this payment method consumers must pay for the electricity they consume in advance. Usually this electricity is purchased in a store and afterwards the customer must update a meter which is installed in the household. When the meter runs out of credit the clients need to purchase more credit. The consumer controls how much to purchase each time. The technology is meant to address a number of problems both from the consumer and the utility side.

From the consumer's point of view prepaid meters allow for flexibility regarding the size and timing of the payment. This is especially relevant for poorer households that are unable to meet larger monthly payments. In addition, consumption is linked with expenditure and this helps consumers to control better their expenditure and the electricity that they use, avoiding debt accumulation. Depending on the type of meter technology it can also offer feedback information to consumers regarding their consumption and therefore allow for better control

of electricity use (Anderson, White, & Finney, 2012; Brutscher, 2011; Jack & Smith, 2015; Qiu et al., 2016).

Prepaid meters also offer a number of advantages to the service providers as transaction costs are reduced and so is non-payment as self-disconnection of non-paying customers is automatic (Jack & Smith, 2016). Meters allow for better peak demand management as information about different tariffs throughout the day becomes readily available. This is especially relevant for renewable energy (Darby, 2012).

However, a number of disadvantages associated with prepaid meters have also been highlighted. From the side of the consumer self-disconnection and self-rationing can occur (Brutscher, 2012b). Self-rationing is when the consumer uses less electricity than is required to cover the household's needs because of inability to pay. This could be particularly the case in months of lower revenues, leading to a seasonality effect in electricity consumption. Self-disconnection occurs when the household remains without electricity for some time due to inability to pay to refill the meter. Self-disconnection can also occur for other reasons irrelevant to income constraints. For example, when an individual runs out of credit at times when it is not possible to purchase more credit. The problems of self-rationing and self-disconnection have been identified especially in studies in developed countries and they can have detrimental effects both for the consumers but also render the suppliers' revenues unpredictable (Howat & McLaughlin, 2012).

The study of the advantages and disadvantages of prepaid meters can draw from standard models of technology adoption but also from non-standard models of decision making including the ones looking at the role of self-control problems and the social context of decision making.

The potential of self-control problems and intra-household dynamics to affect prepayment patterns has been suggested by a number of studies (Jack & Smith 2016; Brutscher, 2011; 2012b), but so far no study has tested these effects in a developing country context. This study aims to fill this gap.

As discussed in Chapter 1 hyperbolic discounting linked to self-control problems as well as intra-household pressures to share money have been linked with inability to save (Ashraf et al., 2006; Bauer, Chytlová, & Morduch, 2012), inability to make upfront costs to acquire new technologies (e.g. fertilizers, health products) in developing countries (Duflo, Kremer, & Robinson, 2011; Dupas & Robinson, 2013), and with a preference for small frequent purchases even when this leads to larger total costs (Attanasio & Frayne 2006). Access to different commitment devices (depending on the underlying limitation) (e.g. credit, saving

devices) has been shown to limit these effects (Dupas & Robinson, 2013). However, little research has been done to see how these findings can inform the effectiveness of billing methods such as prepayment and monthly billing.

Findings from this literature could apply in the study of prepayment patterns in a number of ways.

Prepaid meters are thought to increase consumers' ability to pay since the flexibility of the payment regime allows individuals that face liquidity and income constraints to pay in smaller more frequent amounts (Jack & Smith, 2015). However, this flexibility can also help address self-control problems that could affect an individual's ability to control the level of electricity consumed. In this case the choice of small refill amounts could serve as a commitment strategy to use less electricity at home (discussed in Brutscher, 2011).

At the same time self-control problems, through their direct negative effect on saving, could be impacting the seasonality of electricity use (if such individuals are unable to save during the months of higher revenues). Self-disconnection can also be caused by self-control problems. This occurs when individuals with self-control problems are not able to smooth their income or if they are unable to purchase credit ahead of time to avoid self-disconnection during the night when credit is not available to purchase. Finally, not using the system properly when it is cheaper to consume (when a time-varying tariff scheme is in place) could also be an outcome of self-control problems. As such individuals might not be able to resist the temptation to consume when the tariff is more expensive. Intra-family dynamics can also affect these actions, namely family pressures to share money and different priorities regarding expenditure within the households, through their potentially negative impact on the individuals' ability to save. Coordination issues regarding prepayment amongst family members can also increase the prevalence of self-disconnection.

Brutscher, 2011; 2012b are the only two studies to my knowledge that explore some of the behavioural implications of the way individuals refill their meters. Brutscher, 2011 finds that customers in Northern Ireland refill more often with smaller amounts than expected from a model including the opportunity cost of time and average wages, due to the salience of cost of higher refill amounts. However, this conclusion is drawn through the observation of prepayment patterns. Brutscher, 2012b looks at the determinants of self-disconnection by using metering data in Great Britain and finds that financial considerations are the main drivers. The study also finds that this self-disconnection is very seasonal, and this seasonality is driven by hyperbolic discounting. However, the study does not attempt to identify the factors causing the seasonality of expenditure or what determines the decision to use electricity at times when it is

the most expensive to consume. In addition, no similar research has been done in a developing country setting.

This study aims to fill these gaps by looking at how prepayment patterns for electricity, provided by a solar hybrid mini-grid operating in rural Guinea-Bissau, are affected by a number of socio-economic factors and equipment in use, but also by self-control problems, social pressures to share money, coordination problems and diverging priorities within the households as well as being charged a time-varying tariff. I use actual information on prepaid meter expenditures from a solar hybrid community mini-grid in rural Guinea-Bissau, and compare it to survey elicited information regarding discounting preferences and other relevant characteristics of the household. I examine both how these factors determine the level and frequency of monthly expenditure but also the level of refill amounts. In addition, I look at the drivers of self-disconnection, seasonality of expenditure and usage at times when the customers are charged a higher tariff (between 12 am and 9am), drawing from the same literature. The expenditure patterns of a small group of consumers also charged a higher tariff for their consumption between 7pm to 12 am are also studied.

Findings indicate that prepayment helps address both income constraints as well as self-control problems. Results confirm findings from other studies that overall there is a preference for small and frequent refills (Jack & Smith, 2015; Brutscher, 2011). The level of monthly expenditure is driven positively, amongst other factors, by income levels and using the service for income generating activities. However, lower income households do not undertake more frequent refills. Self-control problems have a negative significant effect on the level of refill amounts (the effect on average monthly expenditure and frequency of refills is also negative but not significant), this indicates that customers with self-control problems use smaller refill amounts as a method to commit to using less electricity at home. Similarly, individuals charged a higher tariff for their consumption between 7pm to 12am choose smaller refill amounts possibly as a method to control their consumption patterns. In addition, there is evidence of an inflexibility on the refill amount chosen, which can be driven by a general tendency of the population to use smaller refill amounts in order to control electricity consumption or by fear of losing larger amounts of credit due to technical problems. Self-disconnection due to inability to pay is driven by financial constraints, however the overall numbers of households reporting to experience self-disconnection commonly is low. Self-control problems or intra-household dynamics do not seem to increase the incidence of self-disconnection or the seasonality of electricity use. Finally, using the meter at times when it is more expensive to consume is also determined by factors irrelevant to income and self-control problems.

These findings are important to consider when designing the specifics of the prepaid method. Namely results advise against the use of a minimum refill amount and in favour of putting in place schemes that will encourage income generating activities at the household level (e.g. credit and rental schemes for appliances).

The study proceeds as follows. Section 2 provides a brief literature review. Section 3 discusses the case study and the data and Section 4 provides the results whilst Section 5 concludes.

2. Literature review

A few quantitative studies have researched into the use of prepaid meters in developed countries. The main areas of focus are comparisons between payment patterns of prepaid meter users to users that are billed on a monthly basis. Brutscher, 2011 finds that households in Northern Ireland that use prepaid meters consume more than households who are billed monthly. He attributes this effect to computational limitations and the salience of larger expenditures. In other words, as clients using prepaid meters refill small amounts they end up spending more. Qiu et al., 2016 in a similar study in the United States find that clients consume less when prepaid meters are used. Both of these studies use the method of matching as in both cases consumers' self-select to the payment method. Jack & Smith, 2016 is the only study to my knowledge that has undertaken a randomized control trial to measure these effects and the only such study undertaken in a developing country (South Africa). Results are similar to the Qiu et al., 2016 study. In other words, Jack & Smith, 2016 find that clients using prepaid meters consume less. They also find that the prevalence of non-payment decreases with prepaid meters. Both studies discuss the potential channels (e.g. information effects, price effects, nudging, costs of self-disconnection, self-control and intra-household control problems) of these effects but they do not attempt to explore them further.

In terms of exploring the limitations that prepayment addresses, Jack & Smith, 2015 look at expenditure information on prepaid meters from Cape Town in South Africa and demonstrate that prepaid meters address liquidity constraints of lower income households. They draw this conclusion by showing that lower income households refill their meters by the end of the week and the end of the month when usually salaries are paid. In addition, they show that poorer households purchase smaller and more frequent amounts of credit. The main

limitation of this study is that it does not collect detailed socio-economic and equipment use information of the customers and it only relies on property values as a proxy of income. In addition, it does not test the effect of self-control problems and intra-household dynamics.

The present study fills this gap by testing the impact of self-control problems and intra-household dynamics on the use of prepaid meters for electricity.

Only two studies to my knowledge try to uncover some of these effects (Brutscher, 2011, 2012b).

Brutscher, 2011 explores the association of expenditure patterns with consumption of electricity in Northern Ireland. The study finds that customers refill more often with smaller amounts than expected from a model including the opportunity cost of time and average wages. And when tariffs increase, individuals maintain the amount they refill with and only increase the number of refills. The author argues that liquidity constraints cannot be the sole explanation behind this pattern, as the same behaviour is also observed for wealthy households. The study concludes that the reason is salience effects, because when customers are forced to increase their refill amounts they decrease their electricity use. The argument that people prefer smaller refill amounts because they are sophisticated about their self-control problems, and they want to commit to lower electricity consumption, is rejected. The author argues that if that were the case, when consumers were forced to increase their refill amounts, they would adjust their electricity use and not decrease it. The study also concludes that the salience of costs is the underlying reasons of why prepaid meters are associated with more consumption.

However, these conclusions are drawn with data observations without including any time preference elicitation measures. In addition, other studies have found that prepayment leads to less electricity use. The contribution of the present study is to include a time preference elicitation measure as well as measures of intra-household dynamics in order to explore prepayment patterns in a developing country setting.

Brutscher, 2012b looks at the determinants of self-disconnection by using metering data in Great Britain and finds that self-disconnection is driven by financial considerations. The main alternatives tested are income effects, forgetting, coordination issues and availability of credit. He discovers that only income effects are significant. The study also finds that this self-disconnection is very seasonal, and the reason behind this seasonality is hyperbolic discounting. However, the Brutscher, 2012b study does not test the effects of self-control problems on self-disconnection overall, and nor does it test the effect of self-control problems on seasonality of consumption.

My research adds to this study by looking at how self-control problems and intra-household dynamics can affect self-disconnection and seasonality of prepayment expenditure in a developing country context. Finally, no study has looked at the changes of prepayment patterns when time-varying tariffs are charged in a developing country setting.

3. Data and methodology

3.1 Case study

This study took place in the semi-urban community of Bambadinca, situated in the Bafatá region in the Northeast part of Guinea-Bissau (See Chapter 1 and 3). Payment data was extracted from clients of a solar hybrid mini-grid operating in the community since November 2014 (see Chapter 3 for a description).

3.2 Prepaid meters and expenditure data

The payment system for the clients of the mini-grid is based on prepaid meters that clients must refill every time they run out of credit. Credit is purchased in the mini-grid station. Clients have top-up cards which are updated according to the amount they purchase each time. These cards are subsequently used to update the meter at home.

The minimum refill amount is 500 FCFA and clients are allowed to refill any multiple of 500. The tariff charged depends on the time of day customers use the service. The lower tariff is charged during the day. From 9 am until 7pm customers are charged 250 FCFA per kWh. This price goes up to 320 FCFA per kWh after 7pm until 12am, and to 560 FCFA per kWh after 12 am until 9am. This tariff scheme was devised to limit pressures on the solar system and reliance on the generators when there is no sunlight available. This is called the ‘normal’ tariff scheme. A ‘social’ tariff scheme was reserved for poor households (as measured by equipment connected). This ‘social’ tariff scheme charges customers the lowest tariff until 12 am. The tariff after 12am is the same for everyone. However, due to an error during client registration only a small number of clients were charged the ‘normal’ tariff and therefore the distinction between the two categories is random and not based on socio-economic criteria.

The meter installed inside the household provides information about the tariff that is being charged. A green intermittent light informs the consumers that the lowest tariff is being charged (250 FCFA per kWh) and a red intermittent light, that the highest tariff is being charged (560 FCFA per kWh) (this light turns to red when the meter is out of credit and to orange when the meter is almost out of credit). Finally, there is a screen displaying rotating information on the date and time, the total energy used so far in kWh, instant power in kW (power of all connected appliances), days of remaining credit with current usage patterns and current credit available. However, in discussions with service operators and households it was clear that consumers relied less on the information displayed in the screen as they found it confusing. The current credit available which is the most relevant information provided, is in a unit other than the amount paid which adds to the confusion (a picture of the meter is shown in the Appendix).

The credit at least in theory is not available for purchase any time of the day. The mini-grid station opens from 9am to 6pm daily and is closed on Sundays. But some activity is also observed outside operating hours and on Sundays.

A comprehensive database regarding the time, date and size of these refills was made available by SCEB. This constitutes the expenditure dataset⁴³. The expenditure information used in this study is until the end of October 2016.

3.3 Survey and time preference elicitation

A background survey was implemented in two waves as the customer base grew. The first wave took place between 26th of January and 29th of February 2016 and the second one between 31st of May and 14th of June 2016. The population of interest are households who receive electricity from the Community Energy Service of Bambadinca. In all cases, the person who makes the decision regarding meter refills was interviewed.

At the time of the second wave of surveys, SCEB had 450 clients in total: 320 were households, 124 businesses and 12 institutions. All household clients of the service at the time were contacted and overall, 312 household clients participated. 259 in the first round and 53 in the second round. Of these, 4 observations had to be dropped as I was not able to identify the

⁴³ There have been some errors in this database, due to some technical problems related to card refill and the updating of meters. However, the database has been monitored closely and corrected by the SCEB personnel and therefore it is assumed that these errors are negligible.

client in the SCEB client expenditure database. This was because some clients shared the same name and could not be distinguished from one another.

The survey was originally written in Portuguese and the enumerator translated orally the questions from Portuguese to the local Portuguese Creole language. Each survey took on average 30 minutes to complete.

I designed a household survey containing information on relevant socio-economic characteristics, household electricity use and the relevant intra-household dynamics. The full survey can be found in the Appendix.

More specifically I measure household coordination issues by eliciting information on the number of individuals that are responsible within the household to make the payments for electricity. Assuming that if there is more than one person responsible coordination issues could arise.

I measure family pressures to share money by directly asking individuals to state the degree to which they feel pressured to share money with other individuals in the household when they have money available. As a measure of priority disagreement within the households I use a similar measure to the measure Bratcher, 2012a;2012b uses to measure the degree of interference. I ask respondents to state the household member that gives a priority on saving money for electricity expenditure and the household member that makes decisions about other expenditure apart from electricity. I subsequently capture the level of disagreement between these two activities. Some disagreement means that the individual that saves money for electricity also makes decisions about other household expenditure, but with someone else. Full saving disagreement means that these two activities are undertaken by different individuals.

Finally, a choice task protocol to elicit discount rates was used, to measure self-control problems, drawing from common practices in the literature (Frederick et al., 2002). This was the same used in Chapter 2 (See Chapter 2).

3.4 Modelling framework

To estimate the drivers of prepayment patterns, the following Ordinary Least Squares (OLS) models are estimated:

$$Y_{averagerefillamount} = a + \beta_x X_i + \varepsilon_i$$

$$Y_{averagemonicthlyexpenditure} = a + \beta_x X_i + \varepsilon_i$$

$$Y_{averagemonicthlyrefillfrequency} = a + \beta_x X_i + \varepsilon_i$$

Where Y_j represents the relevant prepayment patterns (average refill amount, average monthly expenditure, average monthly refill frequency). $\beta_x X_j$ are the relevant observable factors the effects of which I measure (socio-economic characteristics, household electricity use, intra-household dynamics, self-control problems, type of tariff charged), and ε_j is an error term.

Similarly, the following models were constructed to measure the determinants of self-disconnection and frequency with which electricity is used when it is the most expensive to consume (after 12 am). Two measures of self-disconnection were included. Self-disconnection because the household runs out of credit at times when credit is not available to purchase (self-disconnection 1), which is a 3-scale variable (1= never, 2=sometimes, 3=frequently) and self-disconnection due to inability to pay (self-disconnection 2), which is also a 3-scale variable (1= never, 2=sometimes, 3=frequently). The frequency with which electricity is used when it is most expensive to consume is a 4-scale variable (1= never, 2= rarely, 3=sometimes, 4=frequently).

$$Y_{selfdisconnection1} = a + \beta_x X_i + \varepsilon_i$$

$$Y_{selfdisconnection2} = a + \beta_x X_i + \varepsilon_i$$

$$Y_{mostexpensive} = a + \beta_x X_i + \varepsilon_i$$

Finally, the following models measure the determinants of the seasonality of electricity use. I include two measures of seasonality. The first measure (seasonality 1) measures the seasonal variation of electricity use across equally warm months (but with different income availability),

specifically this is measured by the total differences between expenditure levels in March 2016 and June 2016, the second measure (seasonality 2) measures the general variation across all months, specifically this is the standard deviation of monthly expenditure divided by the mean expenditure.

$$Y_{seasonality1} = a + \beta_x X_i + \varepsilon_i$$

$$Y_{seasonality2} = a + \beta_x X_i + \varepsilon_i$$

4. Results

4.1 Descriptive statistics of general household characteristics

Tables 1, 2 and 3 present the relevant sample characteristics regarding demographics, energy use and intra-household dynamics⁴⁴. Table 1 presents the demographics of the sample⁴⁵. As far as household income level is concerned, due to high income variability and the absence of stable sources of income for the majority of households in Bambadinca, I resorted to a direct subjective assessment of household income. The enumerator, who had local knowledge, was asked to choose between four different levels of income classification for each household, following the conclusion of each interview: ‘high income’, ‘medium income’, ‘poor’ and ‘very poor’. Subsequently, roughly 17% of households were classified as ‘high income’, 47% as ‘medium income’ and 36% as ‘poor’. Only one household was classified as ‘very poor’ reflecting the fact that the population of interest are those who have made electricity connections.

⁴⁴ This sample is not directly comparable with the sample in Chapter 4 in terms of demographic characteristics and household expenditures as this chapter includes a larger client population and the prepayment patterns presented here refer to a larger period.

⁴⁵ The sample is not representative of the Bambadinca population, as only households using the electricity service (the target population) were interviewed. But it is representative of the clients of the electricity service, since a large proportion of the population was interviewed.

TABLE 1 SUMMARY STATISTICS FOR RESPONDENT AND HOUSEHOLD CHARACTERISTICS

Number of observations	308	Average age of respondent (years)	41.17
Average household size	11.96	Respondent never had any schooling (%)	20.78
High income household (%)	16.56	Respondent received primary education (%)	32.47
Medium income household (%)	47.08	Respondent received secondary education (%)	37.66
Poor household (%)	36.04	Respondent received university education (%)	9.09
Very poor household (%)	0.32	Respondent engages in commercial activity (%)	56.17
Household receives fixed salary (%)	33.77	Household engages in agriculture (%)	31.73
Household has a female head (%)	16.89	No hardship during rainy season (%)	8.28
Household receives remittances (%)	33.77	Some hardship during rainy season (%)	84.11
Respondent is female (%)	26.30	Significant hardship during rainy season (%)	7.62

Table 2 reports households' energy information. All connected households use lamps and the grand majority uses a TV (70%). The use of fans and fridge is also high. The use of fridge to generate income is also common (31%). This consists mostly to selling cold refreshments or other fresh products. Although households are under different contracts than businesses these type of income generating activities by households are allowed and they are prevalent amongst all income groups. Only 14% of households are currently charged under a 'normal' tariff scheme. On average households have been using the meters for 16 months. In addition, 46% of households were using the service previously to the meter installation and were charged a flat tariff⁴⁶. Finally, in regards to electricity use information prior to the service 33% of households reported that they were connected to Badora⁴⁷ and 27% that they were using a private generator regularly.

⁴⁶ The mini-grid started operating on the 15th of November 2014 with initially 120 clients, through a pilot phase to test the power plant and grid. In this pilot phase the grid was not yet fully operational. In that phase households were charged a flat rate of 3,000 FCFA, regardless of how much electricity they consumed until April 2015 when the meters were installed.

⁴⁷ Private electricity provider before the mini-grid started operating (see Chapter 3).

TABLE 2 SUMMARY STATISTICS FOR ENERGY INFORMATION

Household is charged a 'normal' tariff	13.64%	Household uses lights	100%
Household previously used generator regularly	27.27%	Household uses TV	69.44%
Household previously used Badora	33.44%	Household uses fan	49.34%
Household was previously charged a flat tariff	46.43%	Household uses fridge	35.76%
Household uses a fridge to generate income	31.13%	Household uses computers	17.55%
<i>High income household uses a fridge to generate income</i>	30.61%	Household uses iron	8.94%
<i>Medium income household uses a fridge to generate income</i>	37.06%	Household uses satellite dish	13.58%
<i>Poor household uses a fridge to generate income</i>	22.12%	Household uses DVD	50.33%
Household uses lights to generate income	2.98%	Average wattage installed (W)	665.75%
Households uses other equipment to generate income	0.33%	Average months household is using the meter	16.01

Table 3 reports information on household decision making dynamics, pressures to share money and priority disagreement amongst different household members. All respondents participate in decision making regarding electricity use, 16% decide jointly with someone else in the household and 35% pay to recharge the meter with someone else in the household. As far as priority disagreement is concerned 40% of the surveyed households experience full priority disagreement and in 10% there is only some priority disagreement. Finally, the grand majority reports to be at least under some pressure to share money with others within the household when they have money available.

TABLE 3 SUMMARY STATISTICS FOR HOUSEHOLD DECISION MAKING PATTERNS

Respondent is a decision maker for electricity (%)	100	Respondent reports no pressure to share money (%)	1.67
Respondent decides about electricity with other individuals (%)	15.91	Respondent reports some pressure to share money (%)	53.25
Respondent pays for refills with other individuals (%)	34.74	Respondent reports significant pressure to share money (%)	30.13
Full disagreement on priorities (%)			10.39
Some disagreement on priorities (%)			39.61

4.2 Descriptive statistics of household expenditure patterns

The following graphs show some general patterns of electricity expenditure. Figure 1 reports the frequency for different refill amounts. It becomes clear that there is a preference for 1000 FCFA and in general for smaller refill amounts, which is in line with findings from other studies (Brutscher, 2011; Jack and Smith, 2015). Figure 2 reports the average household expenditure by month. There is high seasonality in expenditure. With higher levels of expenditure in June and the lowest ones in December (April 2015 has the lowest level but this is due to the fact that the meters were still being in the processes of instalment). Interestingly, although the seasonality effect is also present in the case of average refill amounts (Figure 3) and average refill frequency (Figure 4) the effect is less sharp and there is an overall declining trend for the level of refill amounts and an overall increasing trend for frequency of refills. Therefore, overall it seems that as time goes by households resort to refilling smaller amounts more often.

As Figures 5,6 and 7 demonstrate these effects are experienced similarly across all income levels. Overall, the higher income groups always spend more in total and choose higher amounts for their refills than poorer households. However, although the refill frequency is higher for higher income groups in the first months after a few months this refill frequency converges for all income groups (Figure 7). More figures describing patterns of expenditure (by day of the month, time and day of the week), as well as comparison with energy expenditure prior to the service, that are not central to this analysis, are presented in the Appendix.

It is not always possible to understand if this seasonality effect is the outcome of weather or of income effects. The months of higher income availability in the community are June, December and January and of lower income availability August, September and October (rainy season). In terms of when households experience the highest need for electricity

households reported to need more electricity during the warmest period of the year (due to more intense use of fridge and fans), which is the months of March, April, May and June. Less electricity is needed in the colder months starting from the end of November and extending throughout February. That is why it is observed that December and January experience low electricity expenditure levels despite high income availability. The need for electricity during the rainy season varies as some days are very hot and some are cooler.

Therefore, the best way to isolate the potential seasonality effects due to income constraints is to measure the difference in consumption between equally warm months where income availability varies (as described in the previous section).

FIGURE 1 TOTAL NUMBER OF REFILLS FOR DIFFERENT REFILL AMOUNTS (FCFA)

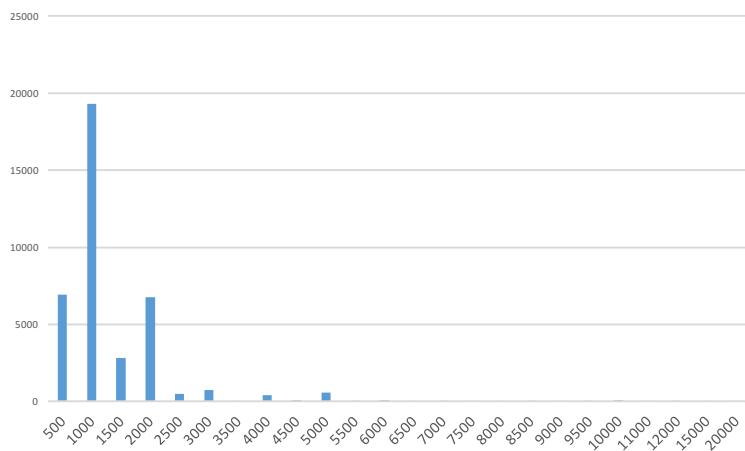


FIGURE 2 AVERAGE EXPENDITURE BY MONTH (FCFA)

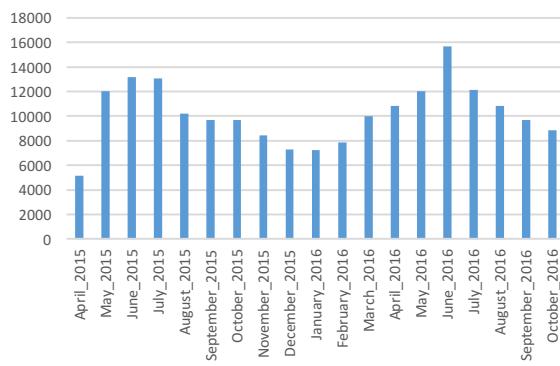


FIGURE 3 AVERAGE REFILL AMOUNT BY MONTH (FCFA)

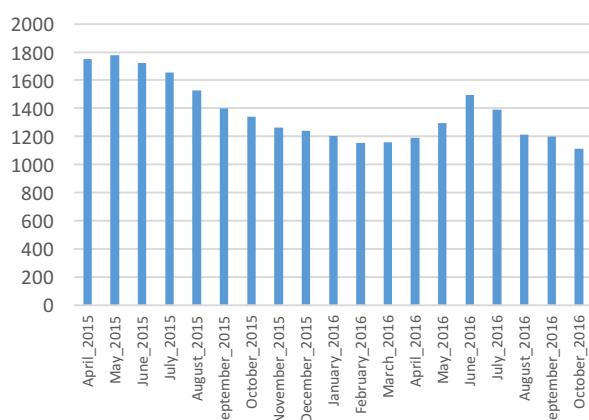


FIGURE 4 AVERAGE REFILL FREQUENCY BY MONTH

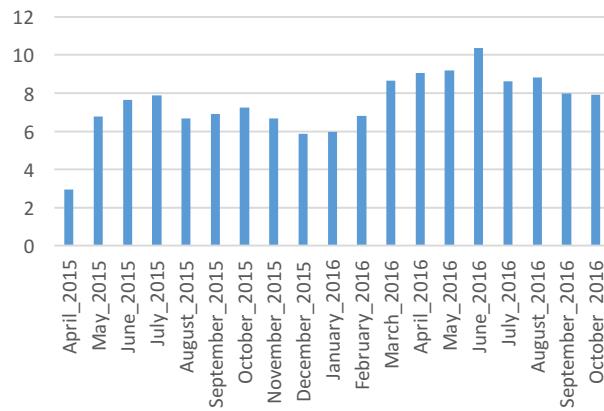


FIGURE 5 AVERAGE MONTHLY EXPENDITURE BY INCOME LEVEL (FCFA)

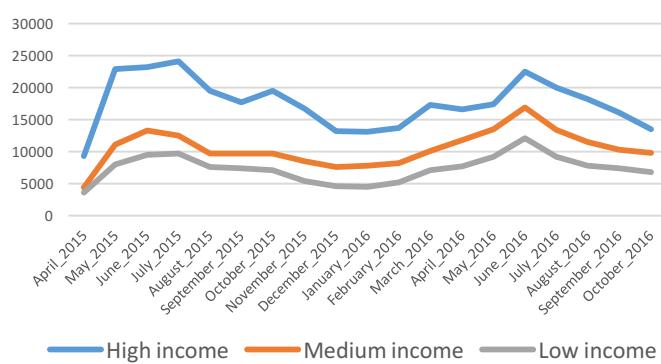


FIGURE 6 AVERAGE REFILL AMOUNT BY INCOME LEVEL (FCFA)

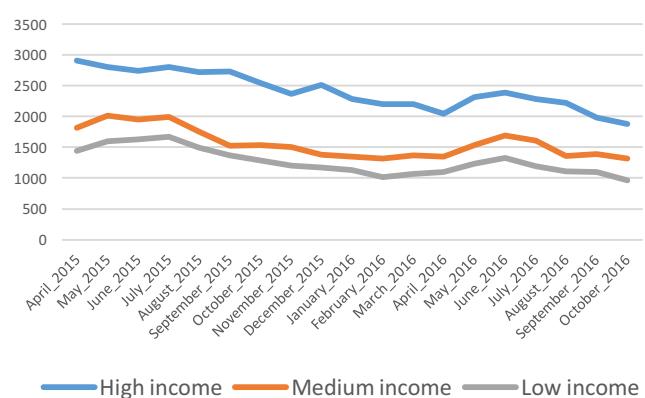
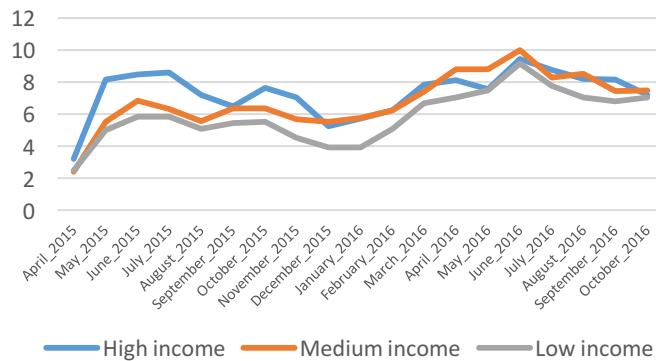


FIGURE 7 AVERAGE MONTHLY REFILL FREQUENCY BY INCOME LEVEL



The average refill frequency per month is reported to be 7.68 (Table 4). This is comparable to patterns described by Jack and Smith, 2015 in South Africa as the average refill frequency per month was reported to be 8.45. Brutscher, 2011 finds this number to be smaller as the average consumer using prepayment in Northern Ireland refills 45 times a year (3.75 a month). The level of expenditure and refill amounts are not comparable between studies because of differences in tariffs and living standards, but overall a preference for both frequent and small amounts has been observed across (Brutscher, 2011; Jack & Smith, 2015).

As noted already refills only occur in one location, which is the mini-grid station. Overall, distance to this refill station varies as some households can be up to two kilometres away. However, the point of purchase is still relatively close for all households in comparison to other case studies where a number of purchase locations are scattered at the city level (Brutscher, 2011).

TABLE 4 DESCRIPTIVE STATISTICS OF EXPENDITURE PATTERNS

	Average	Standard deviation	Minimum	Maximum
Average monthly expenditure (FCFA)	10146.44	9250.99	491.80	68676.92
Average monthly refill frequency	7.68	6.84	0.25	51.29
Average refill amount (FCFA)	1481.88	983.02	596.15	7877.19
Average distance to the refill station in meters	863.82	435.96	33.32	2020.49
Seasonality 1	6224.91	15685.95	-25500	125500
Seasonality 2	0.41	0.24	0	1.43

Seasonality 1= (expenditure June 2016-expenditure March 2016) Seasonality 2= standard deviation of monthly expenditure divided by mean expenditure.

26% of respondents reported being without electricity at least once because of lack of money, and 68% to have been without electricity at least once because they ran out of credit after hours. Only 21% reported that they never consume electricity after 12am.

TABLE 5 SUMMARY STATISTICS OF ELECTRICITY USING PATTERNS

Household never disconnects because of lack of money (%)	74.35	Household never uses electricity when it is the most expensive to consume (%)	21.28
Household rarely disconnects because of lack of money (%)	16.88	Household rarely uses electricity when it is the most expensive to consume (%)	14.54
Household often disconnects because of lack of money (%)	8.77	Household sometimes uses electricity when it is the most expensive to consume (%)	5.67
Household never runs out of credit because the mini-grid station is closed (%)	31.82	Household frequently uses electricity when it is the most expensive to consume (%)	58.51
Household rarely runs out of credit because the mini-grid station is closed (%)	45.78		
Household often runs out of credit because the mini-grid station is closed (%)	22.40		

4.3 Responses to time preference questions

Table 6 reports the descriptive results of the discounting elicitation. 32% of respondents have a monthly discount rate that is lower than 25% for trade-offs now and 51% for trade-offs in a year from now. Mean monthly discount rates are 3.45 for trade-offs now and 2.82 for trade-offs in a year from now. In addition, 34% of the respondents are hyperbolic discounters and 14% are more patient in the future.

Overall, these discount rates are lower than the ones found in Chapter 2. One of the reasons behind this could be that Bambadinca is a semi-urban community and on average households are better off than in most of the more rural communities surveyed in Chapter 2. However, the time preference reversals are higher in the case of Bambadinca, which is harder to explain.

These discounting rates remain higher compared to other studies in the literature both in developed and in developing country settings. For example, Thaler, 1981 finds yearly discount rates to range from 1% to 345% for hypothetical choices, Coller & Williams, 1999 find discount rates for elicitation with real payments between 1 month to 3 months to range from 15% to 25%.

Harrison, Lau, & Williams, 2002 also using actual payments find annual discount rates to be 28%. Andersen, Harrison, Lau, & Rutström, 2008 find an average annual discount rate of 10.1% when also controlling for risk preferences. In a developing country setting studies conducted also find lower discount rates. Bauer et al., 2012 find three-month discount rates in rural India to be 0.244 for current trade-offs, and 0.193 for future trade-offs in elicitation with real monetary rewards and controlling for risk preferences. Anderson, Dietz, Gordon, & Klawitter, 2004 find monthly discount rates to range between 0.6% to 66.9% in Vietnam and Pender, 1996 find discount rates to range between 0.26 to 1.19 in India.

The levels of absolute discount rates are not directly comparable across studies eliciting discount rates in the lab or the field as the time frames and the level of monetary gains or losses vary. For the objectives of this study what is important is to look at within sample variations (Bauer et al., 2012; Thaler, 1981).

The percentages of individuals exhibiting time preference reversals that are more relevant for this study are comparable. My results are very close to findings from Bauer et al., 2012 and Ashraf et al., 2006.

Bauer et al., 2012 find the percent of individuals who exhibit hyperbolic preferences to be 33% and 9.6% to be patient now and impatient in the future. Ashraf et al., 2006 find 25.7%

to exhibit hyperbolic preferences and 14.6% to be more patient in the future. Finally, Dupas & Robinson, 2013 find these numbers to be 16% and 18% respectively.

TABLE 6 DESCRIPTIVE STATISTICS OF ANSWERS TO TIME PREFERENCE QUESTIONS

Discount rates	
Average discount rate now	3.45
Average discount rate in a year from now	2.82
Hyperbolic preferences	33.65%
More patient in the future	13.78%
Discount rate (Now vs 1 month)	Percent of respondents
0.25	32.37
0.75	17.63
1.25	6.73
1.75	9.29
2.25	0.32
2.75	2.88
3.75	3.21
5.5	2.24
9	6.41
11	18.91
Discount rate (12 months vs 13 months)	Percent of respondents
0.25	51.28
0.75	11.86
1.25	4.49
1.75	5.13
2.25	0.32
2.75	2.88
3.25	0.64
3.75	1.60
5.5	0.96
9	2.56
11	18.27

Hyperbolic preferences: higher discount rates in the present than in the future. More patient in the future: lower discount rates in the present than in the future.

4.4 Determinants of prepayment patterns

Table 7 reports the determinants of the relevant prepayment patterns namely the average refill amount, average monthly expenditure and average monthly refill frequency. A table with an explanation of all variable names used in the regressions can be found in the Appendix.

Findings show that prepayment patterns are driven by income constraints as well as self-control problems.

The average refill amount is positively driven by income (being in the medium income group does not have a significant effect, but retains a positive sign), using a fan and using the service of Badora prior to the service and negatively driven by self-reported seasonality of income, being charged the ‘normal’ tariff and experiencing self-control problems (the effect of self-control problems on average monthly expenditure and frequency of refills is also negative, but not significant).

The negative effect of self-control problems on the average refill amount is an indication that individuals with self-control problems refill lower amounts as a commitment to consume less electricity.

The fact that households that are being charged a ‘normal’ tariff are also observed to refill with significantly lower amounts can also be interpreted as an attempt to control electricity consumption. Households charged the ‘normal’ tariff need to be more careful about their patterns of consumption (as they are also charged a higher tariff between 7pm and 12 am). Importantly, although this lower refill level also translates to more frequent refills it does not translate to higher expenditure. This suggests that households adapt their consumption patterns when they are charged a time-varying tariff. This last finding should be interpreted with caution however as the coefficient on the effect on monthly expenditure might be insignificant but it is positive and the sample of households charged a ‘normal’ tariff is small (only 42 households).

Average monthly expenditure is positively driven predominantly by using the fridge for income generating activities, which highlights the important potential of such small-scale income generating activities. Other factors that affect monthly expenditure positively are income (being in the medium income group does not have a significant effect, but retains the same sign), household size, using a fan, being a client of Badora prior to the service as well as by being a female decision maker and experiencing high pressures to share money with other family members. Distance to the refill station and having someone in the household employed in agriculture has a negative effect on monthly expenditure. These effects are the same for

average monthly refill frequency. The only difference is that income has no effect on average monthly refill frequency. This last finding confirms the patterns observed in Figure 7 showing refill frequency to converge across income levels.

Lower income households are therefore not found to undertake refills more frequently in order to offset for lower refill amounts like in Jack & Smith, 2016. This could be due to the fact that distances to the repayment centre are smaller than at the city level and the range of income disparities captured is smaller than those at the city level.

The positive effect of being a female decision maker and experiencing pressure to share money on level and frequency of expenditure could be driven by the fact that these households tend to belong to higher income levels. Possibly this could also be linked to less control of over the electricity consumption of other family members, but there is not enough information to confirm this. Priority disagreements and coordination issues within the household do not seem to affect any of the prepayment patterns.

The regression models control for a number of other variables that were not found to be significant and are not presented in the table. Namely additional characteristics of the household and decision makers (age, schooling, commercial activity, receiving remittances from abroad) other equipment in use (TV, computer, iron, TV antenna), total wattage, using a generator frequently prior to the service, and being charged a flat tariff prior to the meter installation. All the included controls were checked for multicollinearity.

Overall, all models have good predictive power however, this predictive power is smaller for the model looking at the determinants of refill amount (adjusted R-squared 0.14) compared to the models looking at the determinants of monthly expenditure and refill frequency (adjusted R-squared 0.41 and 0.35 respectively). This shows that there are more factors unaccounted for in the model looking at the determinants of refill amount.

Overall, there is a lack of flexibility in increasing the level of refill amounts. For example, higher distance to the refill station seems to be affecting refill frequency negatively possibly due to the increased inconvenience associated with refilling. This is however not offset with higher refill amounts and leads to lower levels of monthly expenditure. In addition, higher levels of monthly expenditure due to the use of a fridge to support income generating activities are undertaken by increasing the amount of refill frequency and not the level of refill amount.

Some explanations suggested by the literature that I do not account for in this model would be that overall smaller amounts are preferred because of the salience of higher refill amounts or that individuals prefer not to purchase higher amounts in fear that they would loose their money due to technical problems associated with the meter (discussed by Brutscher,

2011). Finally, it is possible that the decision maker is choosing lower refill amounts in order to control the electricity use of other household members.

A general tendency of the client population to use smaller refill amounts in order to control electricity consumption is a possible explanation as I have already observed that this is undertaken by at least two types of client groups (those charged a ‘normal’ tariff and individuals with self-control problems).

The second explanation, referring to lack of trust, is also plausible as some technical problems leading to the loss of credit for a number of clients were indeed experienced. In addition, this would explain the declining trends of refill amounts observed in Figures 5,6, and 7⁴⁸. Despite these trends, the time using the meter has no effect on the refill level of the household. But it is possible that as households’ negative experience spreads throughout the community this could affect the refill level decisions of new costumers as well.

The salience explanation, although it cannot be ruled out, would not explain an overall, declining trend on refill amounts at the community level.

⁴⁸ Other factors could be driving this trend. However, a community shock like increased liquidity constraints/ or an overall decline in the income would affect expenditure levels as well, which is not the case.

TABLE 7 DETERMINANTS OF EXPENDITURE PATTERNS

	Average refill amount (FCFA)	Average monthly expenditure (FCFA)	Average monthly refill frequency
Constant	1463.16*** (498.79)	11093.59** (5046.29)	9.99** (4.32)
Hyperbolic	-184.15* (97.41)	-794.93 (910.61)	-0.29 (0.69)
Rich household	803.66*** (228.99)	4853.90*** (1438.72)	1.35 (1.18)
Medium income household	152.37 (105.91)	975.90 (922.95)	0.26 (0.72)
Distance to refill station (log)	21.66 (65.93)	-1118.16* (584.63)	-1.08** (0.52)
Household size	8.15 (11.48)	229.35*** (76.22)	0.12** (0.05)
Female decision maker	1.67 (138.03)	2389.09* (1336.14)	1.57* (0.92)
Seasonality	-248.23* (136.81)	-592.41 (1029.69)	0.52 (0.84)
Agriculture	25.08 (127.35)	-1903.56* (1135.68)	-2.18** (0.88)
Family pressures to share money	-30.13 (124.05)	1826.05* (1120.22)	1.61** (0.81)
Decides with other people	-122.69 (119.87)	-607.74 (1422.80)	0.70 (1.26)
Pays for refills with other people	-51.41 (109.52)	898.96 (1295.23)	0.88 (0.87)
Full priority disagreement	27.63 (142.50)	-1554.19 (1478.15)	-0.22 (1.22)
Some priority disagreement	-79.35 (117.05)	-1045.11 (1064.29)	-0.50 (0.79)
Fan	170.37* (99.97)	1770.90* (907.44)	1.10 (0.73)
Badora	222.20** (111.79)	1446.06* (870.81)	0.61 (0.70)
Fridge for income generation	-35.04 (109.92)	9631.29*** (1063.86)	7.21*** (0.85)
Normal tariff	-266.97** (115.48)	1694.41 (1286.09)	1.94* (1.00)
Adjusted R2	0.14	0.41	0.35
F	0.0000	0.0000	0.0000
N	299	299	299

*p-value<0.1 **p-value<0.05 *** p-value<0.01.

All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported).

All models control for additional characteristics of the household and decision maker (age, schooling, commercial activity, receiving remittances from abroad) other equipment in use (TV, computer, iron, TV antenna), total wattage, using a generator frequently prior to the service, and being charged a flat tariff prior to the meter installation.

Table 8 reports the determinants of self-disconnection. Overall, the predictive power of all models is low suggesting the existence of determinants that have not been accounted for. This is especially the case for the first model looking at the determinants of self-disconnection due to running out of credit when the mini-grid is closed as the adjusted R-squared is as low as 0.02.

Reported self-disconnection due to running out of credit when the mini-grid is closed is negatively determined by age of decision maker and receiving remittances from abroad and positively by the household size. Although the effect of the household size could be capturing some coordination issues, variables capturing household pressures to share money, priority disagreements and coordination issues have no effect.

Reported self-disconnection due to inability to pay is negatively predicted by higher income levels and age of decision maker and positively predicted by distance to refill station, household size and when one of the principle economic activities of the household is agriculture. Neither self-control issues or any of the intra-household dynamics suggested like coordination issues, household pressures to share money, and priority disagreements within the household have a significant effect. This is line with findings from the Brutscher, 2012a study that finds that self-disconnection is driven mostly by income levels. However, results are not directly comparable as Brutscher, 2012a makes no distinction between self-disconnection due to inability to pay and running out of credit due to unavailability of credit.

Time-of-use is also not affected by intra-household dynamics, income or self-control problems. Schooling and age of decision maker have a negative effect on using the service after 12am, which is an indication that there could be some cognitive limitations in understanding the tariff system amongst less educated consumers. Using a fan and a fridge to generate income has a positive effect on using electricity when the higher tariff is charged. There is a reason to use both of these equipment after 12am. As the fridge is used to maintain refreshments cold during the night and the fan is commonly used overnight when temperatures are high.

TABLE 8 DETERMINANTS OF SELF-DISCONNECTION AND TIME-OF-USE

	Self-disconnection 1	Self-disconnection 2	Time-of-use
Constant	1.81*** (0.58)	0.46 (0.43)	4.94*** (1.08)
Hyperbolic	-0.04 (0.09)	0.05 (0.08)	-0.19 (0.15)
Rich household	0.21 (0.16)	-0.30*** (0.11)	0.0006 (0.27)
Medium income household	0.03 (0.10)	-0.18** (0.08)	-0.05 (0.16)
Distance to refill station (log)	0.08 (0.07)	0.11* (0.06)	-0.17 (0.14)
Household size	0.01* (0.006)	0.01* (0.006)	0.002 (0.01)
Age	-0.01*** (0.004)	-0.005* (0.003)	-0.02*** (0.007)
Schooling	-0.02 (0.06)	0.07 (0.04)	-0.19* (0.10)
Remittances	-0.22** (0.09)	-0.05 (0.08)	-0.11 (0.17)
Agriculture	-0.03 (0.11)	0.18* (0.09)	0.19 (0.20)
Family pressures to share money	0.07 (0.10)	0.008 (0.08)	-0.09 (0.17)
Decides with other people	-0.14 (0.14)	0.003 (0.13)	0.28 (0.22)
Pays for refills with other people	0.09 (0.12)	-0.04 (0.09)	-0.15 (0.18)
Full priority disagreement	-0.20 (0.14)	0.17 (0.15)	-0.35 (0.25)
Some priority disagreement	0.15 (0.10)	0.13 (0.09)	-0.11 (0.17)
Fan	-0.06 (0.09)	-0.002 (0.08)	0.54*** (0.16)
Fridge for income generation	0.04 (0.09)	-0.04 (0.08)	0.28* (0.17)
Normal tariff	-0.15 (0.14)	-0.08 (0.10)	0.28 (0.21)
Adjusted R2	0.02	0.11	0.10
F	0.0613	0.0000	0.0000
N	299	299	279

*p-value<0.1 **p-value<0.05 ***p-value<0.01. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported). Self-disconnection 1: Self-disconnection because household runs out of credit: 3-scale variable 1= never, 2=sometimes, 3=frequently. Self-disconnection 2: Self-disconnection due to inability to pay: 3-scale variable 1= never, 2=sometimes, 3=frequently. Time-of-use: Frequency with which electricity is used when it is most expensive to consumer: 4-scale variable 1= never, 2= rarely, 3=sometimes, 4=frequently. All models control for additional characteristics of decision makers (commercial activity, gender, seasonality of income), having someone in the household receiving a fixed salary, other equipment in use (TV, computer, iron, TV antenna), total wattage, using a generator frequently prior to the service, being a client of Badora prior to the service and being charged a flat tariff prior to the meter installation.

As far as the determinants on expenditure level variability due to seasonality of income are concerned overall the models ran had a very low predictive power. Showing that very few of the suggested determinants have an effect. The standard deviation of monthly expenditure is significantly reduced for the highest income households, but no other variable has an effect. The only variable that has a significant negative effect on expenditure level variability is distance to the refill station. Using a fridge for income generating activities has a significantly positive effect⁴⁹. This suggests that overall seasonality of electricity use, for equally warm months, cuts across different income levels and it is not affected by any of the factors that negatively affect the saving ability of individuals (e.g. self-control problems, household pressures to share money and priority disagreements).

TABLE 9 DETERMINANTS OF SEASONALITY OF INCOME ON EXPENDITURE

	Seasonality 1	Seasonality 2
Constant	6978.47 (6138.96)	0.36*** (0.12)
Hyperbolic	-3499.51 (2141.13)	-0.03 (0.03)
Rich household	-684.81 (2968.8)	-0.08* (0.05)
Medium income household	-113.45 (2199.89)	-0.06 (0.04)
Distance to the refill station	-5.12** (2.15)	0.00001 (0.00004)
Household size	261.08 (185.14)	0.0004 (0.002)
Fridge for income generation	7001.43*** (2504.25)	0.05 (0.04)
Adjusted R2	0.0681	0.0065
F	0.0199	0.3818
N	261	274

*p-value<0.1 **p-value<0.05 *** p-value<0.01. All models are ordinary least squares regressions with robust standard errors (coefficient and standard error reported).

Seasonality1= expenditure June 2016-expenditure March 2016.

Seasonality 2= standard deviation of monthly expenditure divided by mean expenditure.

All models control for additional characteristics of decision makers (age, schooling, commercial activity, gender, pressure to share money, seasonality of income), having someone in the household receiving a fixed salary, receiving remittances from abroad, if the household is engaged in agriculture, deciding about electricity with other individuals, paying for refills with other individuals, the level of priority disagreement within the household, other equipment in use (TV, computer, iron, TV antenna, Fan), total wattage, being charged a 'normal' tariff, using a generator frequently, being a client of Badora prior to the service and being charged a flat tariff prior to the meter installation.

⁴⁹ A third measure of seasonality was used which measured the relative differences between expenditure levels in March 2016 and June 2016. Results are not reported here as this model had no significant determinants.

5. Conclusions

This study looks at how prepayment expenditure patterns for electricity provided by a solar hybrid mini-grid operating in rural Guinea-Bissau are affected by a number of socio-economic factors, the equipment used, but also self-control problems, intra-household dynamics as well as being charged a time-varying tariff. These expenditure patterns include the level of monthly expenditure and refill frequency as well as the level of refill amounts. In addition, I look at how these factors affect self-disconnection, seasonality of expenditure and usage at times when the customers are charged the highest tariff. This is the first study to measure the effect of self-control and intra-household dynamics on the use of prepayment in developing countries. A better understanding of the underlying mechanism of expenditure patterns of prepayment will help to both understand the relative advantages and disadvantages provided by the prepayment method and inform the design of such prepayment schemes. Finally, this study contributes to the literature of discounting anomalies as it introduces a new case study regarding the effects of self-control problems.

Overall, results indicate that prepaid meters help address income limitations as well as self-control problems.

Lower income households refill lower amounts and spend overall less for electricity. However, I do not find this to translate in higher refill frequency for lower income households as in other studies (Jack & Smith, 2015). In addition, there is also an indication that individuals experiencing self-control problems due to hyperbolic preferences are able to control their electricity consumption better by refilling smaller amounts, as the refill amounts for individuals with hyperbolic discounting are significantly lower.

Similar patterns are observed for individuals who are charged a ‘normal’ tariff (individuals charged a higher tariff also between 7pm until 12am), which underscores that smaller refill levels are also chosen to control one’s consumption patterns in the presence of time-varying tariff schemes.

Overall, both the effect of hyperbolic preferences and being charged the ‘normal’ tariff on the refill amount is much smaller than income effects.

Using a fridge for income generating activities is the most important determinant of expenditure level. In order to meet the higher level of expenditure these individuals do not increase their refill amounts but their refill frequency. This underlines the important potential for small-scale income generating activities at the household level to help households finance their electricity consumption and also boost the utility revenues. Especially since this activity

is common for all income groups. Other factors that affect expenditure levels positively are the use of fans, being previously a client of Badora, household size, being a female decision maker and experiencing family pressures to share money and negatively, distance to the refill station and being principally employed in agriculture at the household level. All these factors also affect the refill frequency in similar ways.

Lower levels of income lead to higher self-disconnection rates due to inability to pay, but this type of self-disconnection does not occur at all for the grand majority of the clients (74.35%) and only 8.77% report that it happens often. Self-control problems, family pressures to share money, household coordination problems and priority disagreements do not seem to have an effect on self-disconnection, seasonality of electricity use (between equally warm months) or using the service at times when it is the most expensive to consume (after 12am). Using the service at times when it is the most expensive to consume is largely driven by the use of equipment that there is a reason to operate through the night (fridge for income generating activities, fan). However, lack of schooling also drives partly this trend which could be indicating the presence of some misunderstanding regarding the time-varying tariff scheme amongst less educated consumers.

I was not able to control for other factors that have been suggested by the literature to affect the level of refill amounts negatively. These are namely salience effects leading consumers to choose a smaller refill, aversion to risk of loosing the refill amount due to technical issues and strategy to control the consumption of the electricity consumed by other members of the household.

As far as policy recommendations are concerned prepayment does address problems limiting the success of traditional billing methods (e.g. income constraints, self-control problems). Importantly the flexibility of the prepayment method allows consumers, using small-scale income generating activities to finance their electricity consumption, to directly link their revenues with repayment for electricity. Encouraging income generating activities, is overall very important as it can be a way to help costumers pay for their electricity, boost their income and ensure the revenues of the utility. This could happen for example through credit or rental schemes that will help individuals purchase relevant appliances. However, policy makers should take into consideration the potential of these income generating activities to affect the time-of-use patterns, and put pressure on the plant especially if it operates on renewable energy.

Brutscher, 2011 recommends to increase the minimum refill amount to increase salience of total costs and reduce expenditure levels. The finding that individuals choose smaller refill amounts to commit to less electricity use and control their expenditure patterns

in the presence of self-control problems and time-varying tariffs runs against this recommendation.

The evidence that the prepayment method allows individuals to control their consumption patterns is an additional argument in favour of the prepayment method when time-varying tariffs are in place (in addition to the potential information effects Darby, 2012).

The ability to control one's consumption through prepayment could also be one of the reasons behind the reduced consumption observed in a number of studies (Jack & Smith, 2016; Qiu et al., 2016).

Finally, the absence of self-control problems or family pressures effects on self-disconnection and seasonality of electricity use shows that certain interventions like saving schemes, to address self-control problems or other family pressures, to smooth one's income throughout the year would not help reduce seasonality of expenditure and self-disconnection.

These findings overall could apply on other sectors that also use prepayment. For example, prepayment has also been expanding in the water sector (Jack & Smith. 2016). However, this study has also some case specific characteristics that could potentially not apply in a city environment which has higher distances to repayment centres and larger income gaps between users.

Finally, other possible effects like information effects, price effects, nudging (discussed in Qiu et al., 2016) were not the focus of this study, but should be the focus of research in the future in order to explore more fully the effects of prepayment.

6. References

Andersen, S., Harrison, G. W., Lau, M. I., & Rutström, E. E. (2008). Eliciting risk and time preferences. *Econometrica*, 76(3), 583-618.

Anderson, C. L., Dietz, M., Gordon, A., & Klawitter, M. (2004). Discount rates in Vietnam. *Economic Development and Cultural Change*, 52(4), 873-887.

Anderson, W., White, V., & Finney, A. (2012). Coping with low incomes and cold homes. *Energy Policy*, 49, 40-52.

Ashraf, N., Karlan, D., & Yin, W. (2006). Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines. *The Quarterly Journal of Economics*, 635-672.

Attanasio, O., & Frayne, C. (2006). *Do the poor pay more?* Paper presented at the Eighth BREAD Conference, Cornell University.

Bauer, M., Chytilová, J., & Morduch, J. (2012). Behavioral foundations of microcredit: Experimental and survey evidence from rural India. *The American Economic Review*, 102(2), 1118-1139.

Boardman, B., & Fawcett, T. (2002). Competition for the poor. *Liberalisation of electricity supply and fuel poverty: lessons from Great Britain for Northern Ireland. Lower Carbon Futures, Environmental Change Institute. University of Oxford, United Kingdom*.

Brutscher, P.-B. (2011). Payment Matters? -An Exploratory Study into the Pre-Payment Electricity Metering.

Brutscher, P.-B. (2012a). Making Sense of Oil Stamp Saving Schemes.

Brutscher, P.-B. (2012b). Self-Disconnection Among Pre-Payment Customers-A Behavioural Analysis.

Coller, M., & Williams, M. B. (1999). Eliciting individual discount rates. *Experimental Economics*, 2(2), 107-127.

Darby, S. J. (2012). Metering: EU policy and implications for fuel poor households. *Energy Policy*, 49, 98-106.

Duflo, E., Kremer, M., & Robinson, J. (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *The American Economic Review*, 101(6), 2350-2390.

Dupas, P., & Robinson, J. (2013). Why don't the poor save more? Evidence from health savings experiments. *The American Economic Review*, 103(4), 1138-1171.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of economic literature*, 40(2), 351-401.

Harrison, G. W., Lau, M. I., & Williams, M. B. (2002). Estimating individual discount rates in Denmark: A field experiment. *The American Economic Review*, 92(5), 1606-1617.

Howat, J., & McLaughlin, J. (2012). Rethinking prepaid utility service: customers at risk. *Boston, MA, National Consumer Law Centre*.

Jack, B. K., & Smith, G. (2015). Pay as You Go: Prepaid Metering and Electricity Expenditures in South Africa. *The American Economic Review*, 105(5), 237-241.

Jack, B. K., & Smith, G. (2016). Charging Ahead: Prepaid Electricity Metering in South Africa: National Bureau of Economic Research.

McRae, S. (2014). Infrastructure Quality and the Subsidy Trap. *The American Economic Review*, 105(1), 35-66.

Pender, J. L. (1996). Discount rates and credit markets: Theory and evidence from rural India. *Journal of development Economics*, 50(2), 257-296.

Qiu, Y., Xing, B., & Wang, Y. D. (2016). Prepaid electricity plan and electricity consumption behavior. *Contemporary Economic Policy*.

Sharam, A., & Energy Action, G. (2003). *Second class customers: pre-payment meters, the fuel poor and discrimination*: Energy Action Group.

Szabó, A., & Ujhelyi, G. (2014). Can Information Reduce Nonpayment for Public Utilities? Experimental Evidence from South Africa.

Thaler, R. (1981). Some empirical evidence on dynamic inconsistency. *Economics letters*, 8(3), 201-207

7. Appendix

7.1 Explanation of variable names used in regressions

Definition	
Hyperbolic	Dummy; 1 = higher discount rates in the present than in the future
Rich household	Dummy; 1=household belongs to the highest income category
Medium income household	Dummy; 1=household belongs to the medium income category
Distance to refill station (log)	The natural logarithm of distance to refill station in meters
Household size	Household size
Female decision maker	Dummy; 1= decision maker for electricity is female
Seasonality	Self-reported hardship during rainy season (3 scales 1=do not experience hardship at all)
Agriculture	Dummy; 1= household engaged in agriculture
Remittances	Dummy; 1= household receives remittances from abroad
<i>Age</i>	Age of decision maker for electricity in household (in years)
Schooling	Schooling of decision maker for electricity
Family pressures to share money	Dummy; 1=a lot of pressure to share money with other household members (self-reported)
Decides with other people	Dummy; 1= respondent decides about electricity with other individuals
Pays for refills with other people	Dummy; 1= respondent pays for refills with other individuals
Full priority disagreement	Dummy; 1= the individual that saves money for electricity is not the one that makes decisions about other household expenditure
Some priority disagreement	Dummy; 1= the individual that saves money for electricity also makes decisions about other household expenditure, but with someone else
Fan	Dummy; 1=household uses a fan
Badora	Dummy; 1= household was using the Badora service prior to connecting to the mini-grid
Fridge for income generation	Dummy; 1= household uses a fridge for income generation activities
Normal tariff	Dummy; 1= household is charged a 'normal' tariff

7.2 Meter images⁵⁰

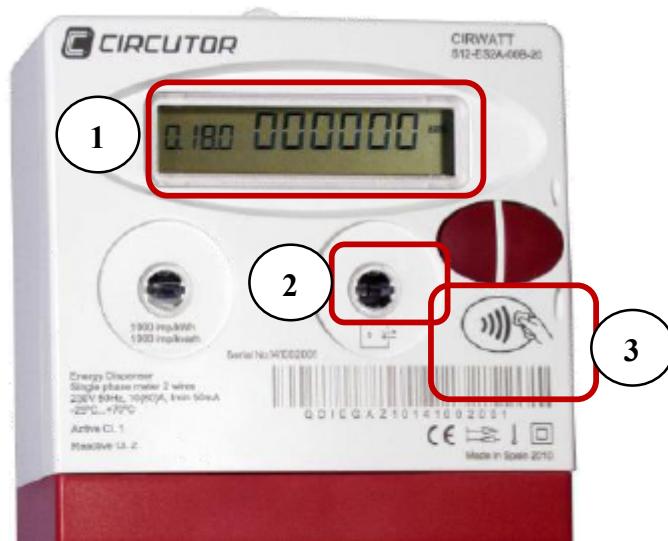


FIGURE 1 ELECTRICITY METER: 1: ROTATING SCREEN, 2: LED LIGHT, 3: CARD READER

- 1) Rotating screen: informs the consumer about the date and time, total energy used so far in kWh, instant power in kW (power of all connected appliances), days of remaining credit with current usage patterns and current credit available.
- 2) Led light: three colours warning the consumer about tariff schedule and availability of credit (see Table 1)

⁵⁰ Images from the utilization manual of Trama TecnoAmbiental tta

TABLE 1 THE MEANING OF THE DIFFERENT LIGHTS OF THE METER

Colour	Meaning
No colour	Normal tariff (320 FCFA per kWh)
Red	Out of credit
Orange	Almost out of credit
Intermittent green	Low price (250 FCFA per kWh)
Intermittent red	High price (560 FCFA per kWh)

3) Card reader (See image below)

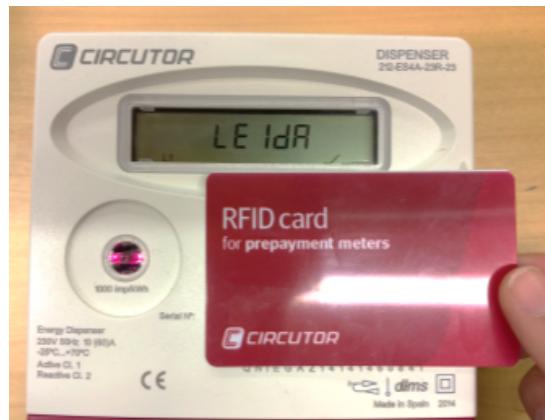


FIGURE 2 METER ACTIVATION. THE PREPAID CARD IS USED TO TOP-UP THE METER EACH TIME THE HOUSEHOLD RUNS OUT OF CREDIT

7.3 Other expenditure patterns

Figures 3, 4 and 5 show expenditure patterns per day of the month, day of the week and time of the day. Expenditures drop by the end of the month. In addition, as the mini-grid officially does not sell credit on Sundays, expenditures are higher on the day before and after. However, there are still substantial expenditures occurring on Sunday. As far as time of the day is concerned the bulk of expenditures occur in the evening right before closing hours. This is probably due to the fact that at this time demand for electricity increases. Also by the end of the day there is more money available.

FIGURE 3 TOTAL AMOUNT SPENT PER DAY OF MONTH (FCFA)

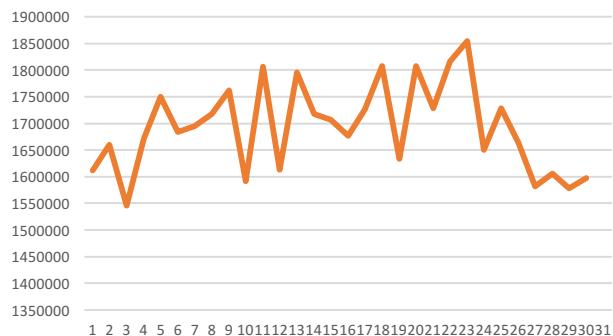


FIGURE 4 TOTAL AMOUNT SPENT PER DAY (FCFA)

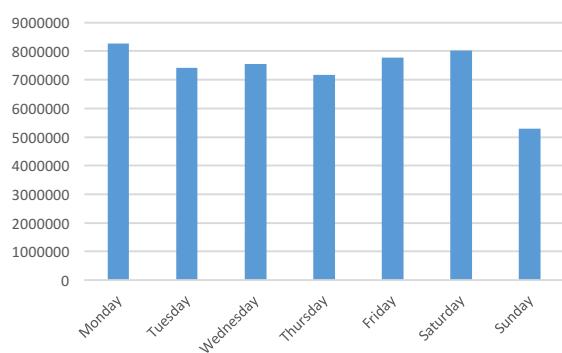


FIGURE 5 TOTAL AMOUNT SPENT PER TIME OF DAY (FCFA)

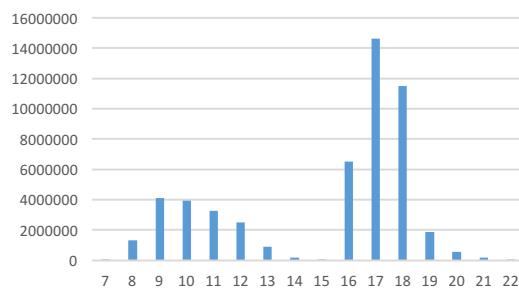


Table 2 presents the average expenditure in Bambadinca for electricity and electricity substitutes prior to the commencement of the mini-grid service (elicited in the survey presented in Chapter 3). Current average monthly electricity expenditure (10,146 FCFA) is lower than the previous average monthly expenditure of households for electricity substitutes and electricity combined (11,295 FCFA) and much lower than it used to be for electricity (Badora, frequent use of generators) (29,563 FCFA).

However, the average expenditure of household previously using only electricity substitutes (e.g. battery powered lamps, candles etc.), which is the grand majority of Bambadinca, was lower (7,591 FCFA).

This indicates that overall the mini-grid service has not drastically increased the previous expenditure patterns for energy for the population of Bambadinca. However, the idea that access to electrification can lead to a reduction in expenditure compared to previous spending patterns is not confirmed for the case of cheap electricity substitutes.

TABLE 2 AVERAGE MONTHLY EXPENDITURE IN BAMBADINCA FOR ELECTRICITY AND SUBSTITUTES PRIOR TO THE SERVICE

	General population	Clients
Households connected to Badora or using generators frequently (FCFA)	29,563	29,067
Household only using electricity substitutes (FCFA)	7,591	8,581
All households (FCFA)	11,295	

7.4 Survey draft

Note to interviewer: Ask: “Who makes the financial decisions and decisions regarding the electricity in this household? Can I talk to this person?”. If not available ask: “When can I come back to talk to that person?”.

If you can not talk to this person, especially if that person does not want to be interviewed, or if anyone else in this family prefers to answer this questionnaire, try to insist that the participation of this person in this questionnaire is very important to us.

After that communicate the following information:

We are conducting a survey in your community that is part of a research initiative carried out by a PhD student at the London School of Economics and Political Science, a university in London, in partnership with ‘TESE’ an NGO working in Guinea-Bissau on infrastructural projects, including energy. The purpose of the questionnaire is to study the community energy service of Bambadinca.

These questions should take around 30 minutes to complete.

Your answers will be strictly confidential and will not be shared with anyone else. Answers will only be used anonymously for research purposes.

Participation is voluntary you can refuse to participate without providing any explanation and without any consequences. If you agree to participate in the survey you have the right to stop whenever you want.

Your participation is very important to us. We will use the information that you and other families give us to better understand the factors affecting the success of the community energy project, for the advancement of academic knowledge. This knowledge could serve future energy policies in Guinea-Bissau.

Do you have any questions? **May I continue interviewing you?**

Your response will have no influence over the way the energy service is being offered to you (tariffs etc.)

It is very important that you give honest answers, not over or under state the answers, as if the information we collect is not true, the outputs of the survey will not be beneficial to your community or Guinea-Bissau.

Which family member decides about the service repayments	
Which family member pays for the service repayments	
Client number	
Client name	
Name of respondent	
What is the gender of the respondent?	Female Male
What is your principal economic activity? <u>(Note to interviewer:</u> you can note more than one)	Public servants. Specify _____ Private employees. Specify _____ Services/ Commerce. Specify _____ Agriculture. Specify _____ Fishing. Specify _____ Animals. Specify _____ Other. Specify _____
How many people live in this household including you? By household I mean all individuals who normally live and eat their meals together in this household and share their expenses. <u>(Note to interviewer:</u> Here in order to make sure we get the right response make sure to make a short conversation about what the relationship of each member is to the respondent. Example: Begin by asking who else lives here)	
What is the ethnicity of the household?	Fula Mandinga Balanta Beafada Papel Cabo-verdiana Other. Specify _____
What is your age? <u>(Note to interviewer:</u> If they don't know their age or if they seem to be giving you the wrong answer take a note of the age they seem to have. As a clue, ask them what is the age of their eldest son)	
What is your education level?	No schooling Primary schooling Secondary schooling Superior schooling Other. Specify _____

Did your household use the Badora service before connecting to the service of ‘Bambadinca Sta Claro’?	
Did your household use a generator regularly before connecting to the service of ‘Bambadinca Sta Claro’?	
When you have money available are you pressured to share it with people inside your household?	Not at all A little bit A lot
Which family member saves to meet repayments for the services?	
Which family member decides about other family expenditures apart from electricity?	

Time preference questions

Note to interviewer: Introduce by saying: “I will ask you to answer some hypothetical questions regarding your preferences for receiving money in different times”:

Current trade-offs

If someone offered you to receive 1,000 FCFA guaranteed today, or 1,500 FCFA guaranteed in 1 month, what would you prefer?	Today In a month
(<u>Note to interviewer:</u> Continue asking only if answer above is ‘Today’ otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 2,000 FCFA guaranteed in 1 month, what would you prefer?	
(<u>Note to interviewer:</u> Continue asking only if answer above is ‘Today’ otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 2,500 FCFA guaranteed in 1 month, what would you prefer?	
(<u>Note to interviewer:</u> Continue asking only if answer above is ‘Today’ otherwise stop and move to the following page)	Today In a month

If someone offered you to receive 1,000 FCFA guaranteed today, or 3,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 3,500 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 4,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 4,500 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 5,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 8,000 FCFA guaranteed in 1 month, what would you prefer?	
(Note to interviewer: Continue asking only if answer above is 'Today' otherwise stop and move to the following page)	Today In a month
If someone offered you to receive 1,000 FCFA guaranteed today, or 12,000 FCFA guaranteed in 1 month, what would you prefer?	

Future trade-offs

If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 1,500 FCFA guaranteed in 13 months what would you prefer?	12 months 13 months
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 2,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 2,500 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 3,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 3,500 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 4,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 4,500 FCFA guaranteed in 13 months what would you prefer?	

(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months
If someone offered you to receive 1,000 FCFA guaranteed in 12 months, or 5,000 FCFA guaranteed in 13 months what would you prefer?	
(Note to interviewer: Continue asking only if answer above is '12 months' otherwise stop and conclude the interview)	12 months 13 months

What is the gender of the household head?	Male Female
How many household members are between 0-16 years old?	
Do you have children that are currently attending school?	Yes No
What is the principal economic activity of your household? (Note to interviewer: you can note more than one)	Public servants. Specify _____ Private employees. Specify _____ Services/ Commerce. Specify _____ Agriculture. Specify _____ Fishing. Specify _____ Animals. Specify _____ Other. Specify _____
Does any member of the family receive a fixed salary?	Yes No
Is your household negatively affected during the months when there is less income availability in the community? (August, September, October)	Not at all A little bit A lot
Does your household receive money from abroad?	Yes No

Energy use questions

Do you use lamps in your household? <u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many lamps do you use?	
How many hours per day do you use these lamps? <u>Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use televisions in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many televisions do you use?	
How many hours per day do you use these televisions? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use fans in your household? <u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many fans do you use?	
How many hours per day do you use these fans? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use fridges in your household? <u>Note to interviewer:</u> If 'No' move to the next page)	Yes No
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How many fridges do you use?	
How many hours per day do you use these fridges? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use computers in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many computers do you use?	
How many hours per day do you use these computers? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use electric irons in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many electric irons do you use?	
How many hours per day do you use these electric irons? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use satellite dishes in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
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How many satellite dishes do you use?	
How many hours per day do you use these satellite dishes? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use DVDs in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many DVDs do you use?	
How many hours per day do you use these DVDs? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use Mobile chargers in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
How many Mobile chargers do you use?	
How many hours per day do you use these mobile chargers? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Do you use radios powered by electricity in your household? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
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How many radios powered by electricity do you use?	
How many hours per day do you use these radios? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

Does your household use other equipment? <u>(Note to interviewer:</u> If 'No' move to the next page)	Yes No
Specify	
Quantity	
How many hours per day do you use these equipment? <u>(Note to interviewer:</u> if they prefer to report per week take a note)	Per Day _____ Per Week _____ Other _____ Don't use Can't tell

To you use the service for income generating activities?	Yes No
If 'Yes' what type of activities?	Light Fridge Other
With what frequency do you undertake these activities?	Per day Per week Other
Are there months that you need more electricity?	
If 'Yes' what are these months?	
Are there months that you need less electricity?	
If 'Yes' what are these months?	
How often are you left without credit in you meter because you are unable to pay?	Never Rarely Often
How often are you left without credit in you meter because the mini-grid station is closed?	Never Rarely Often

How often do you use the service between 12am and 9am?	Never Rarely Sometimes Always
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Questions for the interviewer

In your opinion what is the income level of this household?	High income Medium income Poor Very poor
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Chapter 6

Conclusions

This thesis demonstrates that even in the context of rural Guinea-Bissau with a population facing severe income constraints there is high demand for electrification. This demand can be untapped with the right delivery models and payment methods particularly as lump sum costs, seem to constitute one of the biggest barriers to adoption and proper repayment.

Chapter 2 shows how credit and rental schemes can significantly increase adoption of solar home systems, Chapter 3 shows that proximity to the grid which significantly reduces the variable costs of connection leads to increased connections. Chapter 3 also indicates that despite the high demand there was almost no connections (in the first year of operation) amongst the poorest income group and Chapter 5 demonstrates that prepayment for electricity allows individuals to address income constraints and to finance their electricity consumption through small-scale income generating activities. This last finding points to the recommendation that rental and credit schemes for relevant appliances should be considered in these contexts to encourage income generating activities.

One of the motivations of this thesis is to test if certain findings from behavioural economics and the social capital literature, namely regarding the role of discounting anomalies on technology adoption and the role of trust for technology adoption, can apply in the case of electrification access in developing countries. This is in order to enrich our understanding of the barriers and drivers of electrification access in developing countries.

Income constraints seem to pose the main and most common barrier on adoption and to define energy using patterns. However, some of the findings suggest that electrification access can be informed by non-standard models of behaviour.

Chapter 2 provides some evidence that individuals exhibiting hyperbolic preferences have a preference for credit schemes. One explanation behind this is that credit is preferred by individuals with hyperbolic preferences as they see it as a form of commitment. In addition, lack of trust for actors within the community leads to a lower preference for delivery models that entail monthly repayments (credit and rental). This is possibly due to the lack of a social structure to rely upon in case one is unable to meet the monthly repayments.

Chapter 3 demonstrates that social capital as expressed in trust for ones' neighbours, has a positive effect on connections through the informal expansion of the grid, whereby households use their neighbour's infrastructure to connect to the service and reduce their

upfront costs of connection. Trust for one's neighbours is understood to play a positive role in the informal expansion of the grid as neighbours need to come to an agreement to share the associated costs or to allow each other to use their infrastructure.

Chapter 5 demonstrates that prepayment for electricity can help individuals with self-control problems manage their electricity consumption by choosing smaller refill amounts. A similar pattern is observed for individuals facing an additional time-varying tariff (a higher tariff between 7pm and 12 am).

Another objective of this thesis is to demonstrate if and how electrification access case studies can help to strengthen empirical findings from other contexts.

Chapter 2 confirms a number of findings from the discounting literature that observes the actual choices of consumers between different energy consuming products in order to infer implicit discount rates (e.g. Revelt & Train, 1998; Hauseman, 1979; Allcott & Wozny 2014). By observing consumer trade-offs between different intertemporal payments this study shows the validity of these methods and the replicability of the findings (high discount rates and the systematic variation of discount rates between different time intervals and between different individuals) in the context of demand for different delivery models of SHS.

Chapter 4 also confirms certain findings from other contexts regarding the accuracy of expenditure reporting in surveys (higher accuracy with the use of the 'specific' period), but also finds some differences (general over-reporting instead of under-reporting of expenditure found in other studies) (Beegle et al., 2012; Angrisani et al., 2015). In addition, this chapter proposes the use of energy expenditures as a general case study to test the effect of different aspects of survey design on expenditure elicitation by using real expenditure information as a comparison. This is because in contrast to other recurring household expenditure, information on real energy expenditure is becoming increasingly available to researchers, both in developed and developing countries (e.g. Brutscher, 2011; Qiu et al., 2016; Jack & Smith, 2016).

This thesis is hoping to motivate interest for future research. The use of larger sample sizes and opportunities for field experiments in future studies can help confirm and explore further some of the findings of this research, but also to look at other issues pertinent to electrification access.

For example, test other aspects of survey design and theories of response strategies. Explore more fully the effects of prepayment for electricity by testing the role of information, price effects and nudging. As well as explore in more detail the effects of time-varying tariffs (e.g. randomize across a bigger range of time-varying tariffs). Explore the effects on demand of other characteristics of delivery models for electricity (e.g. weekly repayments, flexible

repayments) and how they interact with individual characteristics and to study the effect of these on actual repayment patterns. And finally, isolate the different potential channels through which peer effects can impact electrification.

New opportunities will arise in the future as detailed information on electricity use patterns will become increasingly available with the increased take-up of smart technologies.

6.1 References

Allcott, H., & Wozny, N. (2014). Gasoline prices, fuel economy, and the energy paradox. *Review of economics and statistics*, 96(5), 779-795.

Angrisani, M., Kapteyn, A., & Schuh, S. D. (2015). Measuring Household Spending and Payment Habits: the Role of Typical and Specific Time Frames in Survey Questions, in Christopher D. Carroll, Thomas F. Crossley, and John Sabelhaus, *Improving the Measurement of Consumer Expenditures. Studies in Income and Wealth, University of Chicago Press*, 2015.

Beegle, K., De Weerdt, J., Friedman, J., & Gibson, J. (2012). Methods of household consumption measurement through surveys: Experimental results from Tanzania. *Journal of Development Economics*, 98(1), 3-18.

Brutscher, P.-B. (2011). Payment Matters? -An Exploratory Study into the Pre-Payment Electricity Metering.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. *The Bell Journal of Economics*, 33-54.

Jack, B. K., & Smith, G. (2016). Charging Ahead: Prepaid Electricity Metering in South Africa: National Bureau of Economic Research.

Qiu, Y., Xing, B., & Wang, Y. D. (2016). Prepaid electricity plan and electricity consumption behavior. *Contemporary Economic Policy*.

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of economics and statistics*, 80(4), 647-657.

Images from the field

FIGURE 1 THE BAFATÁ CITY POWER PLANT THAT USED TO ELECTRIFY THE WHOLE REGION NOW OPERATES WITHIN THE LIMITS OF BAFATÁ CITY



FIGURE 2 NIGHT IMAGE OF THE CITY OF BAFATÁ WHEN THE POWER PLANT IS NOT OPERATING



FIGURE 3 A SOLAR HOME SYSTEM INSTALLED ON THE ROOF OF A HOUSEHOLD (LOCATED IN A VILLAGE IN THE REGION OF BAFATÁ)



FIGURE 4 A HOUSEHOLD USING A SOLAR HOME SYSTEM IN A VILLAGE IN THE BAFATÁ REGION OFFERS MOBILE CHARGING SERVICES TO NEIGHBOURS

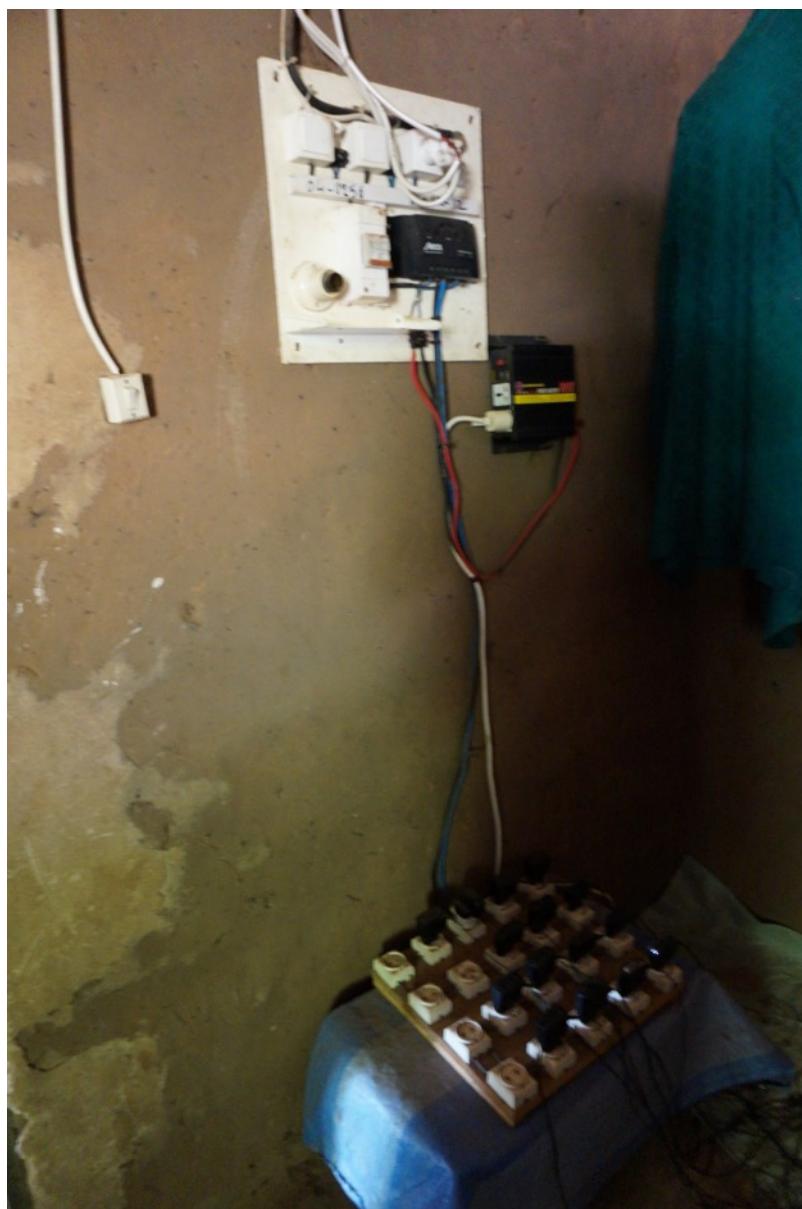


FIGURE 5 DIFFERENT TYPES OF DWELLINGS IN BAMBADINCA: ZINC ROOFS INDICATE A HIGHER INCOME LEVEL THAN ROOFS MADE OF STRAW



FIGURE 6 ABANDONED INFRASTRUCTURE IN BAMBADINCA THAT WAS LATTER INCORPORATED TO THE MAIN GRID



FIGURE 7 INSTALLATION OF THE SOLAR PANELS IN THE MINI-GRID STATION IN BAMBADINCA



FIGURE 8 CONSTRUCTION OF THE MAIN GRID IN BAMBADINCA



FIGURE 9 IMAGE OF A NEIGHBOURHOOD OF BAMBADINCA WITH THE MAIN GRID IN PLACE



FIGURE 10 THE MINI-GRID STATION IN BAMBADINCA



FIGURE 11 ENTRANCE OF THE MINI-GRID STATION IN BAMBADINCA



FIGURE 12 METER INSTALLED WITHIN THE HOUSEHOLD OF A CLIENT OF THE SERVICE IN BAMBADINCA. THE GREEN LIGHT INDICATES THAT THE CHEAPEST TARIFF IS BEING CHARGED

