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Estimating the effect of (mobile) banking coverage on installed off-grid solar photovoltaic capacities in countries of sub-Saharan Africa

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ABSTRACT

Affordable access to electricity has long been found to be a key lever for social and economic development. Over 600 million people in sub-Saharan Africa (SSA) still lacked such in 2016. Given the pertaining issues in grid extension, off-grid solar photovoltaic (PV) applications promise a cheap and scalable way to provide those households without access to the grid with electricity. Research on the diffusion of solar PV applications and other renewable sources of energy suggests, that a lack of financing options and access to financial services poses a hurdle for households to invest into such technologies. The success of off-grid solar PV applications across SSA over the past years coincides with a surge of mobile bank accounts. This dissertation attempts to answer the question, if the diffusion of solar PV applications was impacted by an increased access to financial services through traditional and/or mobile bank accounts. To do so, data on installed solar PV capacities and the percentage of the population using traditional or mobile bank accounts across 38 countries of sub-Saharan Africa in 2011, 2014 and 2017 are analyzed in two cross-sectional regression models. The findings suggest that a 1% increase in the percentage of the population owning a bank account increases installed solar PV capacities between 0.15 MW for any bank account in 2014 and 0.44 MW for mobile bank accounts in 2017. However, these results display a high degree of uncertainty, which is mainly related to issues of data availability as well as potentially omitted variables in the employed models. More research is required to overcome uncertainty and potentially unravel causal mechanisms at play in order to inform policy makers and development agencies about the potential win-win combination of mobile bank accounts and off-grid electrification.

Keywords: Solar PV; Sub-Saharan Africa; Mobile Banking; Financial Inclusion

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1. INTRODUCTION

1.1 Background

Access to affordable sources of energy is crucial to the development of countries and households (González-Eguino, 2014: 378-379). Running machinery, cooking, lighting rooms before and after dark or charging phones all require sources of energy. For most of these energy needs, electricity is required. Providing people with access to electricity has been a crucial component of governments across Africa for a long time and still is today. In 2016, approximately 940 million people globally lacked access to electricity with almost 600 million in sub-Saharan Africa (SSA) alone (Our World in Data, 2020). In 2018, only 26% of rural households in SSA had access to electricity, relying mostly on traditional fuels for cooking and heating (IEA, 2020). In 2017, almost 400.000 people likely died prematurely due to the effects of indoor air pollution from cooking with solid fuels (Our World in Data, 2020). Despite general progress in means of infrastructure, establishing reliable energy grids, that have provided the population of developed countries with electricity for decades at low prices, still poses a huge problem to many governments in sub-Saharan Africa.

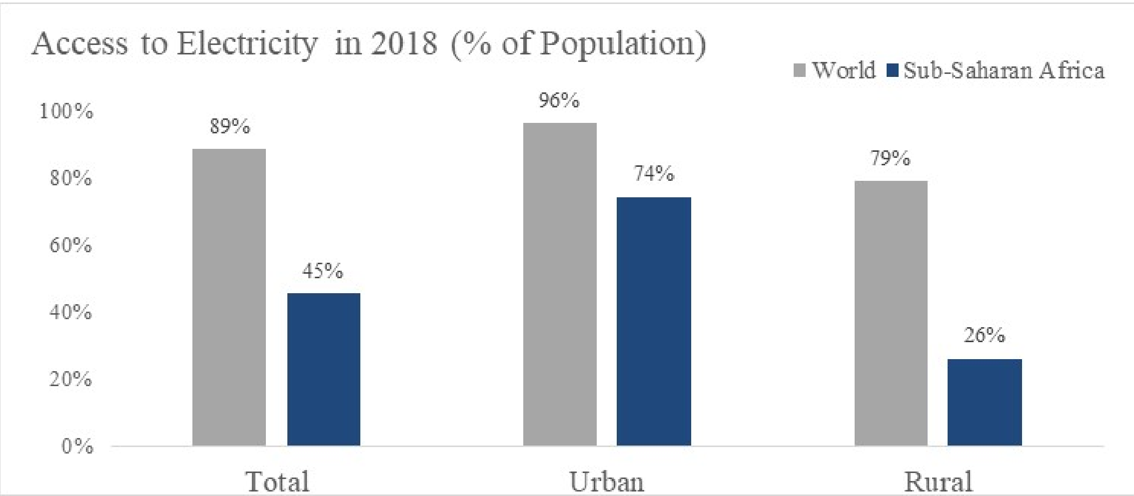


Figure 1 - Comparing Access to Electricity in sub-Saharan Africa and the World, Source: IEA 2020, own elaboration

For those still lacking access to electricity via the grid, off-grid technologies have become the main hope of electrification. The IEA predicts, that of all people gaining access to electricity between 2017 and 2030, 30% will do so through solar photovoltaic (PV) technology and another 30% through mini-grids (IEA, 2019: 28). While initial applications of off-grid energy generation were expensive and mainly geared towards development projects with substantial funding, costs per installed Megawatt (MW) of solar PV systems have decreased by over 60% in Africa between 2012 and 2016 down to a minimum of 1.30USD per Watt with the global average at 1.80USD per Watt (IRENA, 2016).

Today, a diversity of solar applications ranging from pico solar lamps to full-scale solar-home-systems and household appliances are available across African countries. Despite advances in prices, investments are usually required to finance upfront cost – in regions of Africa where income and savings are rare, this poses a challenge to the advancement of solar PV applications.

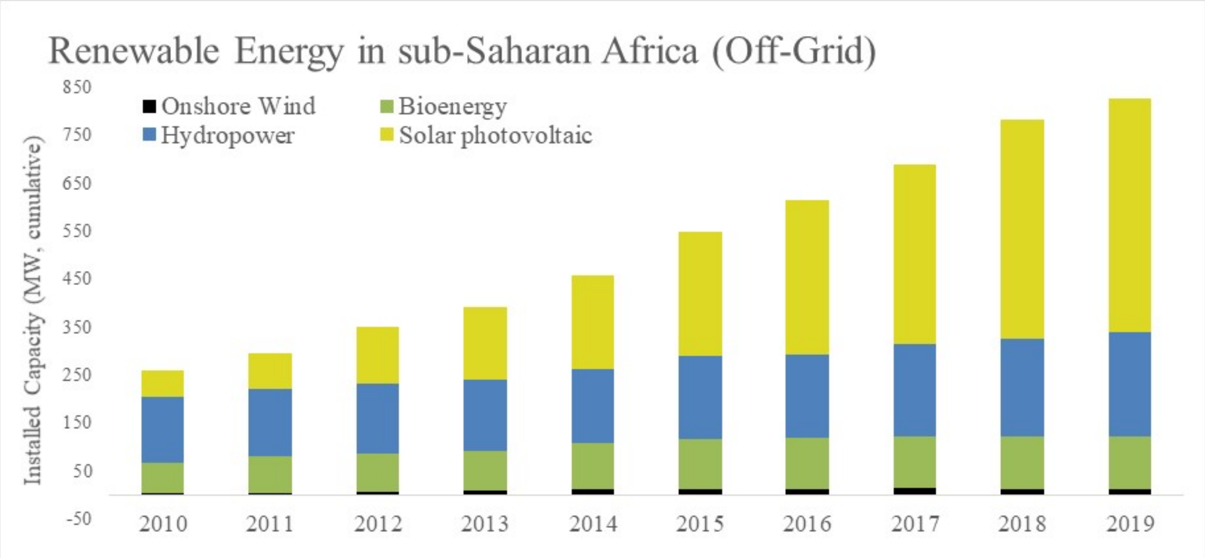


Figure 2 - Off-Grid Energy Generation in sub-Saharan Africa, Source: IRENA 2020, own elaboration

The need for financing options coincides with a surge of mobile bank accounts in Africa. Just in the past decade, over 400 million mobile accounts have been created across sub-Saharan Africa (GSMA, 2020). While these applications were often limited to simple functions such as transferring and receiving money as well as a basic infrastructure to withdraw cash, providers are beginning to include financing options for their customer base as well.

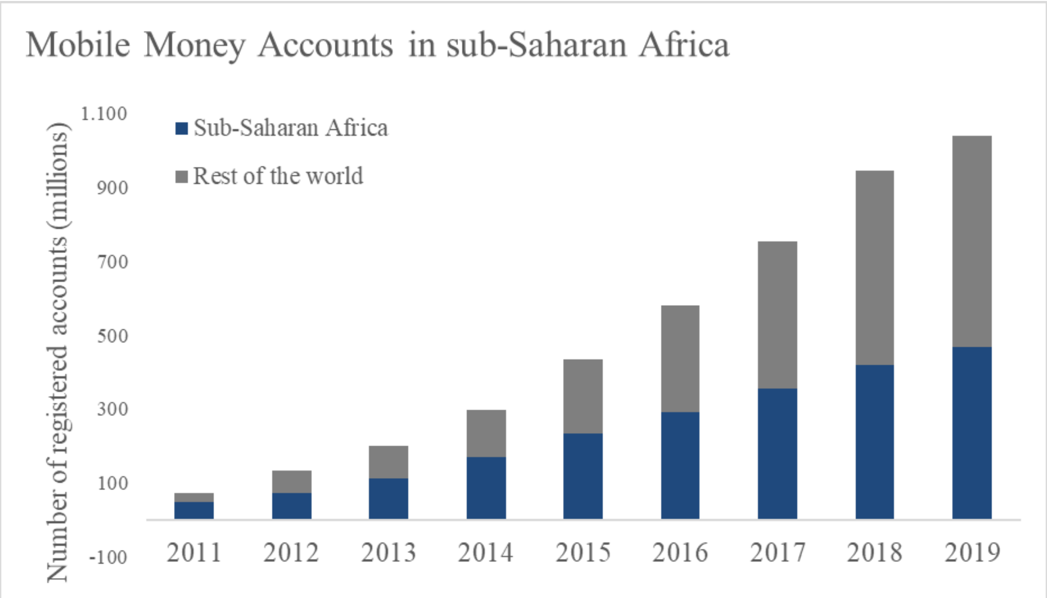


Figure 3 - Number of registered Mobile Money Accounts in Sub-Saharan Africa, Source: GSMA 2020, own elaboration

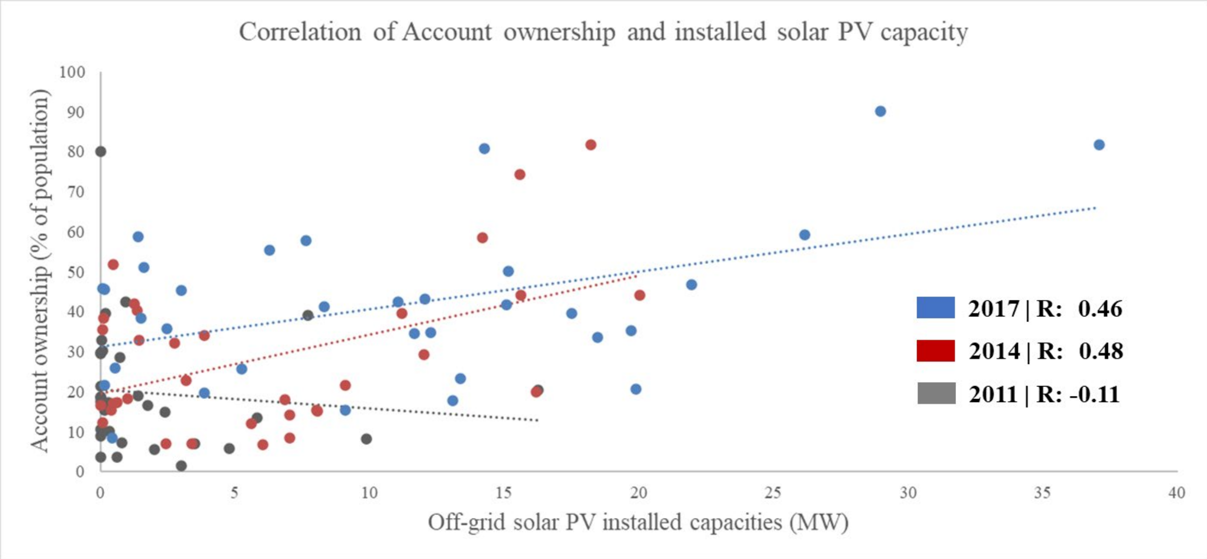
One solution aiming to tackle the issue of financing for solar photovoltaic (PV) applications are pay-as-you-go or "PayGo" models, where consumers provide a minimal upfront payment, receive the desired application and then pay daily or weekly amounts to repay the initial loan over a period of multiple years. Spearheading the charge is Kenya's largest mobile network operator Safaricom. When purchasing a phone or SIM-card from Safaricom, customers automatically receive a mobile bank account at M-PESA, Safaricom's mobile bank. All M-PESA customers are then able to purchase solar PV appliances at M-KOPA, the solar PV subsidy of Safaricom. According to their own reports, M-KOPA has so far "sold over 750,000 off-grid solar systems, providing 3 million individuals with clean, safe lighting solutions" (M-KOPA, 2020).

The puzzle of interest for this dissertation is, if there is a causal link between the surge of mobile banking and installed solar PV capacities in countries of sub-Saharan Africa related to the effects of financial inclusion or if companies such as M-KOPA simply explore a pre-existing customer base that had no access to their solar PV products before.

1.2 Theoretical and substantive justification

A substantive body of literature has already assessed the potential and applications of renewable energy in sub-Saharan Africa (see e.g. Bazilian et al, 2012; Karekezi, 2002; Moner-Girona et al, 2006). Most research conducted has so far focused on promoting or inhibiting domestic factors of specific countries in SSA. While these conditions might provide reasons for the diffusion of certain new technologies, little research has yet been conducted on the impact of financial inclusion on technology diffusion as the main point of interest was, how technology can foster financial inclusion and not vice versa (see e.g Andrianaivo & Kpodar, 2012).

This dissertation seeks to complement existing literature by looking at an example of financial inclusion – i.e. mobile banking applications – fostering the diffusion of a new technology – i.e. solar PV applications. Figure 4 shows a simple correlation of account ownership and installed off-grid solar PV appliances in countries of SSA for 2011, 2014 and 2017. Except for 2011, the correlation is strong and positive which warrants further research.



The topic is important in a real-world application for two main reasons: Energy Poverty and Climate Change Mitigation. Although endowed with huge potential for renewable energy generation, about half of SSAs population still has no access to electricity at home (IEA, 2020). A lack of access to electricity can have negative effects on public service provision, productivity, education and health (González-Eguino, 2014: 382-384). Generating electricity through decentral, renewable sources could bridge current problems related to central energy provision. Regarding climate change, the growing energy consumption of SSAs population will pose a significant threat to world climate if based on traditional means of producing electricity. Identifying the promoting or inhibiting factors at play is thus crucial for domestic and international policymakers to target the growth of renewable energy in a timely and efficient manner. If levers to foster financial inclusion by promoting mobile banking also have a positive follow-up impact on renewable energy capacities, it could further boost these important topics on a policymaker's agenda.

1.3 Research question

Using a quantitative approach, this dissertation aims to estimate the effect of mobile banking coverages in SSA on installed off-grid solar PV capacities, and thus to answer the following research question:

"What is the impact of (mobile) bank account coverage on installed off-grid capacities of solar PV applications in countries of sub-Saharan Africa?"

To do so, the following hypothesis will be tested:

> *In a comparison of sub-Saharan African countries in 2011, 2014 and 2017, those with a higher coverage of (mobile) bank accounts among the population will also show higher levels of*

installed off-grid PV capacities when compared to those with a lower coverage of (mobile) bank accounts.

Testing the hypothesis is approached in two steps. First by estimating the general effect of bank account ownership at either a financial institution or a mobile banking provider and second by differentiating between those parts of the population with only an account at a financial institution or only a mobile money account.

1.4 Structure

Chapter two of this dissertation features a literature review on technology diffusion, renewable energy applications and financial inclusion in countries of SSA. The main goal of this review is to establish a theoretical framework to help answer the research question. To do so, factors influencing the diffusion of technology in general and solar PV in specific are assessed in order to derive dimensions which need to be controlled for when comparing the diffusion of solar PV applications across countries. Second, effects of financial inclusion in general and mobile banking in specific on developing countries are analyzed to identify potential causal mechanisms from financial inclusion to the diffusion of solar PV technology in countries of SSA.

In the third chapter, a framework to operationalize the theoretical findings is established, data availability and imputation are discussed regarding potential measurement errors and data used for the regression models is described. Last, the employed regression models and the general analytical approach is presented.

Following operationalization, chapter four presents results as well as limitations of the different regression models and discusses their ability to answer the research question at hand.

Finally, chapter six concludes by lining out some recommendations for future research and summarizing the results.

2. LITERATURE REVIEW

2.1 Diffusion of technology & renewable energy applications

The broader concept of technology diffusion has a long-standing tradition to explain the spreading of a new technology within and across markets from an economic perspective. In a key article to provide a theoretical base for the diffusion of technology, Paul L. Stoneman defines it as "[…] the process by which innovations (be they new products, new processes or new management methods) spread within and across economies." (Stoneman, 1985: 1). Jacobsson and Johnson use a similar definition to develop a framework for renewable energy diffusion in general (Jacobsson and Johnson, 2000). They propose to complement neoclassical economic perspectives of relative price changes and the individual firm action with a technology specific innovation system, consisting of actors, networks and institutions to assess diffusion rates (Jacobsson and Johnson, 2000: 629, 638).

While useful as a starting point, the fact that their work is heavily focused on OECD countries limits the applicability to SSA, as the idea of replacing old technology with an emerging one is especially important in countries where issues are not related to power-supply but rather to sustainability. Still, the discussed inhibiting factors and comparisons of incumbent, pre-existing systems versus emerging ones need to be observed in countries of SSA as well, as institutional, financial and technological "lock-in effects" (Jacobsson and Johnson, 2000: 633) can also apply on a different scale, where legislations, corporations or other actors favor the extension of fixed grids over off-grid energy provision. It is also worth noting that lock-in effects described for larger systems by Jacobsson and Johnson (2000) may also apply to individual households in a certain way, when deciding to switch from traditional sources of energy to modern solutions, such as solar PV.

Eder, Mutsaerts and Sriwannawit complement these works by taking the perspective of individual households in their case study of a Swedish energy company distributing biogas powered mini-grids in rural Uganda (2015). After conducting interviews with households in the focus-area of the provided technology, they develop three main dimensions influencing the adoption and thus diffusion of said technology in rural Uganda: Technological, Economic and Social (Eder et al, 2015: 50). The technological dimension features the perception towards and awareness of the technology by relevant customers. This starts with the advantages related to electricity – which most households were aware of. But interviews showed that next to perceived reliability and advantages over the status quo, information campaigns on applications, risks and functionality also play an important role for households to consider a new technology (Eder et al, 2015: 50-51). The economic dimension of technology diffusion in this study is broken down into *Affordability*, *Payment Systems*, *Investment Cost* and *Appropriate Tariffs*. *Affordability* relates to a company's decision to offer products where the populace is likely able to afford them. *Payment Systems* refer to the type of system used to make payments for a technology – for a technology to diffuse successfully, this should be as compatible as possible to the currently used systems. *Investment Cost* describes the initial investment required for a household or individual to purchase the technology and *Appropriate Tariffs* relate to the need for companies to find a usage price that reflects the household's or individual's willingness to pay for the service offered. Interestingly, the authors found that in rural Uganda, individuals often believe that "western" technologies should generally be free of charge for them (Eder et al, 2015: 51). Finally, the social dimension reflects the need to collaborate with local actors for a technology to diffuse successfully. Here, the authors highlight partnerships with local experts, a required dialogue with local inhabitants, the need to use local communication channels as well as the necessity to manage the user's expectations (Eder et al, 2015: 52).

Despite the potentially limited scalability of a study conducted in rural Uganda to other countries of sub-Saharan Africa, the findings presented by Eder and his colleagues (2015) hint at many important aspects to consider when developing a framework for technology diffusion generally. It shows that differences in the potential user-base of a technology between countries, be they economic, educational, cultural or social need to be monitored and controlled for when trying to establish a model in a cross-country comparison.

Bawakyillenuo (2012) approaches the diffusion of solar PV in Ghana, Kenya and Zimbabwe from a social perspective, using the Social Construction of Technology (SCOT) framework. He finds that the interplay of favorable economic conditions, political landscapes, international influences and powerful agents promoting solar PV has led to a successful diffusion in Kenya and Zimbabwe when compared to Ghana (Bawakyillenuo, 2012: 420). Similarly, Ahlborg and Hammar (2014) show that drivers and barriers to renewable energy technologies in rural Tanzania and Mozambique mostly lie with national actors during planning and implementation of projects.

Taking a more micro-economic perspective, Ketlogetswe and Mothudi (2009) assess the feasibility of small-scale solar projects for different households in Botswana. They find that next to aforementioned conditions, little flexibility in financing schemes and repayments for loans still pose a main problem for households when investing in solar PV applications (Ketlogetswe and Mothudi, 2009: 1678). In line with these findings, Lemaire (2011) argues that fee-for-service concessions in South Africa promise financial feasibility. However here, grid connection is far more advanced than in Botswana, thus providing additional revenue streams for providers (e.g. through feed-in tariffs). In a comparison of eight case studies across Rwanda, Tanzania and Malawi, Barry, Steyn and Brent (2010) also find, that the availability of finance was a major constraint to the implementation of different technologies (Barry, Steyn & Brent, 2010: 6).

The reviewed literature shows that the general dimensions to consider in the diffusion of renewable energy applications are very comparable across studies. However, an important aspect is that both, a user-perspective as well as a provider or system-perspective, are required to assess technology diffusion in any country and thus a cross-country comparison. These findings help to develop a framework when assessing the diffusion of solar PV applications in countries of sub-Saharan Africa and trying to isolate the impact of (mobile) bank account coverage on it.

Additionally, the findings of reviewed studies clearly indicate, that financial constraints often pose a major hurdle to the diffusion of renewable energy technologies and solar PV applications. The question at hand is, if mobile banking helped overcome these issues in some countries already, thus leading to a more successful diffusion of off-grid solar PV applications.

2.2 Financial inclusion and mobile banking

The World Bank's Global Findex Database measures financial inclusion according to four sets of criteria: (1) Account ownership & usage; (2) Savings behavior; (3) Borrowing and (4) Insurance products (Demirguc-Kunt & Klapper, 2012: 8). Here, financial inclusion is measured from a perspective of usage rather than supply, where indicators like branch-density, cost of service or service entry-barriers would be assessed. Household-based estimates like the World Bank's Findex Database are especially useful when trying to dissect who is using financial services and for what reasons.

Financial development has been shown to increase income for the poorest and reduce income inequality (see e.g. Beck, Demirguc-Kunt & Levine, 2007). More generally, financial inclusion has shown to drive economic growth in general by providing access to credit, thus allocating capital to productive areas formerly not covered by the system, as well as the access to saving accounts or deposits. Here, additional savings are theoretically injected into the financial system, thus allowing the additional capital to be invested into productive means (Sethi & Acharya, 2018: 371-372).

In a study on the effects of mobile banking in rural Uganda, Munyegera and Matsumoto (2016) find, that households using mobile money applications also show significantly higher household consumption in food, non-food basics, education and social contributions (Muneyegera & Matsumoto, 2016: 136). The main mechanism they identify for this increased consumption is remittance payments (Muneyegera & Matsumoto, 2016: 131-132). In their sample, households using mobile banking applications receive higher and more frequent remittances when compared to non-user households (Muneyegera & Matsumoto, 2016: 135). They argue that the most likely reason for this difference is the ease and cost of transferring payments from one location to another with mobile money applications compared to former ways (Muneyegera & Matsumoto, 2016: 137). These findings align with another study on the impact of mobile phone penetration and financial service provision on household consumption in Ghana (Abor, Amidu & Issahaku, 2018).

Similarly, Ouma, Odongo and Were (2017) find, that financial services provided through mobile phones positively affect savings behavior on a household level, using data from Kenya in their savings estimation model (Ouma, Odongo & Were, 2017: 31). Here, they find that both the likelihood of saving at all as well as the amount saved per household increase for those households using mobile banking applications (Ouma et al, 2017: 33). Given, that Kenya is a frontrunner in mobile money, these results may be limited in their applicability across countries of SSA for now. On the other hand, Kenya in its' advanced stage of mobile phone and mobile banking penetration could also serve as a good example of where other countries of SSA could be heading.

The available literature shows that financial inclusion in general and mobile banking in particular can raise household consumption as well as income through various mechanisms and increase household savings in different countries across SSA. Any one of these effects could potentially explain a higher diffusion rate of solar PV applications in countries with a higher coverage of (mobile) bank accounts if this dissertation finds it to be true.

2.3 Linking financial inclusion and technology diffusion

When linking financial inclusion to the diffusion of technologies, multiple possible causal pathways emerge. Figure 5 aims to capture three possible causal pathways, which will be discussed. Note, that these pathways take a demand-side perspective, and therefore only assess the impacts of financial inclusion on households or individuals, and how these could translate into a higher demand for solar PV applications. This follows the assumption, that while there are supply-side factors likely to influence the diffusion of solar PV applications in general, these are probably not influenced by or have an influence on financial inclusion but can be controlled for separately in the statistical analysis of this dissertation.

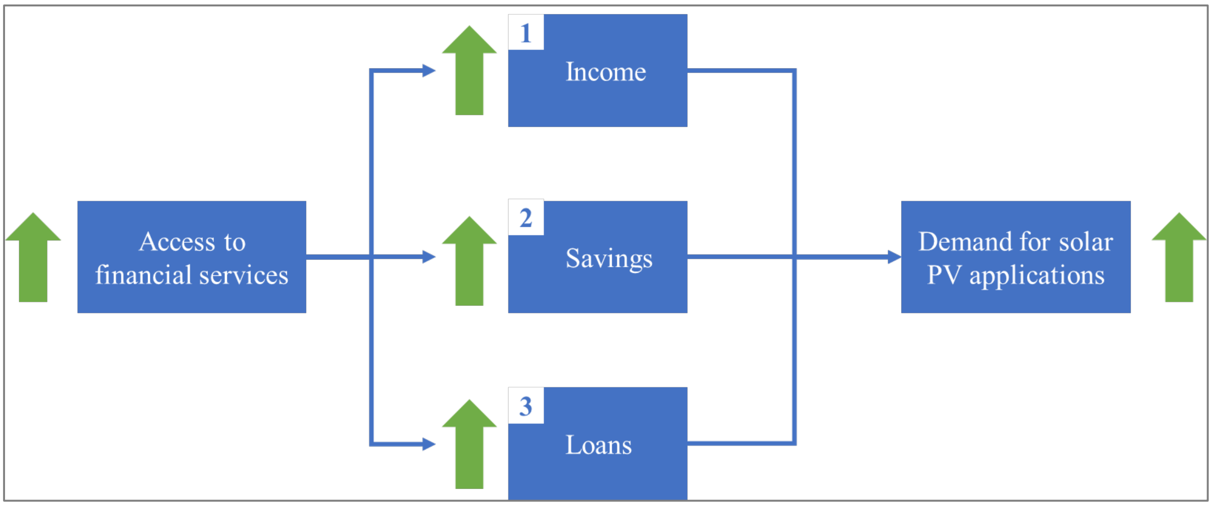


Figure 5 - Causal pathways from Financial Inclusion to Solar PV Applications - Source: Own elaboration

The first possible pathway assumes that by accessing financial services, household income is likely to rise which then also increases the demand for solar PV applications. The impact of access to financial services on household income was already discussed in the first part of this literature review (see e.g. Beck et al, 2007; Muneyegera & Matsumoto, 2016). Multiple studies from different countries in SSA show, that higher income also translates into a higher likelihood of investing into renewable energy technology (see e.g. Guta, 2020; Rahut, Behera & Ali, 2017).

A second option would be for households to save more in total and more frequently, as observed by Ouma, Odongo and Were (2017) in Kenya, when accessing mobile financial services. The likelihood of households investing into said applications should be higher when more savings are available to cover upfront cost.

The third option for financial inclusion to potentially impact the demand for solar PV applications would be through a higher availability and usage of loans by households. If households can access loans, those could be used to either cover the whole cost of investing into a solar PV application or to cover the upfront investment required in certain payment modalities. In their review of case studies across Africa, Barry et al (2010) also showed, that a lack of access to loans by rural households still posed a constraint on the adoption of renewable technologies, as conditions for these had to be negotiated by implementing development agencies rather than a standard cooperation between resellers and mobile banking operators (Barry et al. 2010: 6). A study in rural Ethiopia uncovered, that access to credit did indeed positively affect the likelihood of households to purchase renewable energy technologies (Guta, 2020).

To summarize, the literature review has shown, that while a multitude of factors influence the diffusion and adoption of renewable energy technologies like solar PV, constraints in financing the respective technology have posed a significant barrier to households in the past. Financial inclusion through mobile banking can theoretically overcome these constraints by increasing income and savings on a household level as well as providing access to loans which could be used to invest into said applications. As this link has not been the subject of many studies so far, shedding light on the impact of financial inclusion through mobile banking on solar PV diffusion could help to inform policy-makers, corporations and researchers alike on potential causal pathways and thus areas of focus to further promote the electrification of SSA.

3. OPERATIONALIZATION

3.1 Data collection & availability

As the diffusion of solar PV applications is the main variable of interest, this dissertation uses installed electricity capacities of off-grid solar PV applications in megawatt (MW) as the dependent variable. Data is obtained from IRENA (2020) through an online query-tool, which is available on a yearly basis.

For the independent variables, two main sources are used. First, the World Development Indicator (WDI) database (2020) provides information on the percentage of the population aged 15 or older with an account at either a financial institution or a mobile-money provider. This indicator is used to capture, "traditional" bank accounts as well as mobile bank accounts, thus covering the whole bandwidth of financial inclusion related to bank accounts. Data on this indicator is available for 2011, 2014 and 2017 only. The Financial Inclusion Database (2020) is used to compute two more indicators for mobile banking, i.e. the percentage of the population aged 15 or older with a mobile money account and "traditional" banking, i.e. the percentage of the population aged 15 or older with an account at a financial institution. The respective indicators of the financial inclusion survey do not differentiate between those parts of the population which <u>only</u> use a mobile bank account or <u>only</u> an account at a financial institution. However, as one of the aims for this exercise is to differentiate the effect of mobile banking on installed solar PV capacities, these indicators are computed as follows:

1. *Percentage of population (aged 15 years or older) with <u>only</u> a mobile bank account:*
   Subtract the percentage of the population which have a traditional (financial institution) bank account, including those which also have a mobile money account, from the percentage of the population which have a traditional OR mobile money account.
2. *Percentage of population (aged 15 years or older) with <u>only</u> a traditional account:*
   Subtract the percentage of the population which have a mobile money account, including those which also have a traditional bank account, from the percentage of the population which have a traditional OR mobile money account.

As data on mobile bank accounts is only available for 2014 and 2017, these indicators are limited to two periods.

Using these main indicators, the next step is to define the base units of observation. In this case, all 48 countries of SSA. However, data availability is limited and while imputation can help overcome some of these limitations, it would be questionable to include countries into the analysis where no data is available at all.

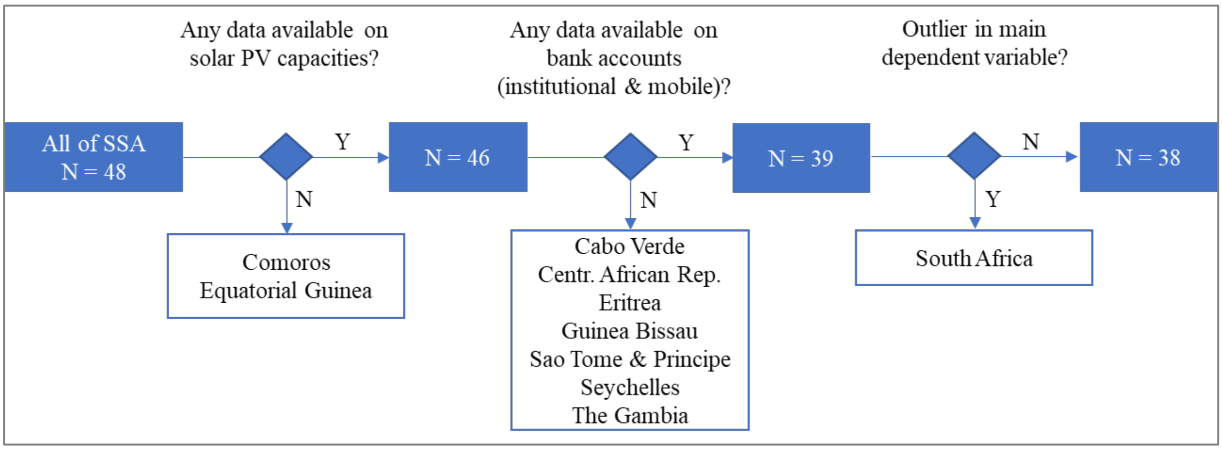


Figure 6 - Exclusion of countries with no data in main variables, Source: Own elaboration

Figure 6 illustrates the logic of excluding countries because of missing data in the main variables of interest. In the first step, those countries are excluded where no observations of installed solar PV capacities are available between 2011 and 2018. This applies to two countries: Comoros and Equatorial Guinea. The second step relates to data on financial inclusion. Here, those countries are excluded where no information is available on either the percentage of the population with a mobile or institutional bank account. It applies to seven countries, thus limiting the number of countries of this analysis to 39.

Finally, to deal with outliers in one of the main variables, South Africa is also excluded from the analysis, as total installed PV capacities amount to 2.561 MW in 2017 – more than double of all other countries' capacities combined. This step reduces the total number of countries in this analysis to 38. As financial inclusion indicators are only available for three periods (2011, 2014 and 2017), the total number of observations – assuming missing datapoints can be imputed successfully – is 114 or 76 for those indicators only available in 2014 and 2017.

In order to include other factors potentially influencing the diffusion of solar PV technology in SSA, this dissertation follows the general logic employed by Eder et al (2015) to group controls into the following: (1) Technological, (2) Economic and (3) Social. However, as this analysis is based on secondary data instead of household surveys, and thus cannot measure perception towards solar PV applications as such, proxies which are likely to impact that perception are used.

Related to the technological dimension, this analysis controls for the percentage of population with access to electricity, assuming that households in those countries with an accessible grid or other established forms of generating electricity are less likely to switch to solar PV applications. Data on this indicator was obtained from the World Development Indicator Database (2020). Additionally, the percentage of individuals using the internet will be used as a proxy for the general technological development of a country, assuming that a population with a larger share of internet users is also more likely to adopt new technologies like solar PV applications. Data for this indicator was obtained from the International Telecommunication Union (2020). Other indicators like road-density or mobile network coverages were also considered here but ultimately rejected in order not to overload a regression with limited data availability in the first place.

To control for economic differences between countries, this study includes Gross National Income (GNI) per capita, in current US Dollar using the World Bank's Atlas method (2020). This is assuming, that in those countries with a higher GNI, technologies like solar PV applications are more likely to diffuse effectively when compared to those with lower GNI. The World Bank's Atlas Method helps to smooth fluctuations in exchange rates and prices which is especially useful in some countries of SSA, where currencies are very volatile over time. As a second economic dimension, the consumer affordability of electricity indicator from the RISE framework is used (2020). The indicator consists of three sub-indicators measuring cost of a subsistence consumption, the affordability of connection fees as well as the availability of a mechanism to support low-volume consumers (RISE, 2020). This indicator could cause a potential issue with simultaneity, as both the cost of a subsistence consumption as well as the connection fee are potentially lower in solar PV applications and would thus be impacted by larger shares of solar PV capacities in a country. However, the currently very low percentage of electricity generated through solar PV across the sample is unlikely to impact it in a substantial manner. It is therefore more likely to capture the effect of a low affordability index on installed solar PV capacities, where those countries in which electricity is generally less affordable are more likely to adopt technologies like solar PV applications.

The social dimension of this analysis is captured through two more indicators. First, secondary school enrolment rates are employed to estimate differences in education between countries. This assumes, that those populations with a higher degree of education are more likely to be aware of the mid- and long-term economic and health benefits of renewable energy technologies over traditional ones and thus more likely to invest into those technologies. Data for this indicator is obtained from the World Bank Database (2020). The second social indicator is another index from the RISE framework (2020) assessing the support for stand-alone electricity systems in countries. This index checks for the existence of a national support program, financial incentives as well as the standards and quality for the systems under such a framework (RISE, 2020). Support of governments for stand-alone systems is likely to promote the diffusion of solar PV applications through multiple channels and therefore an important factor to consider in this analysis (see e.g. Bawakyillenuo, 2012).

Table 1 summarizes all control indicators used as well as their predicted impact on the main dependent variable and the respective data source. See Appendix 3 for links to the data sources.

Variable	**Predicted dep. Var. Relation**	**Source**
Technological Controls		
Population with access to electricity (% of total)	Negative	World Development Indicators
Individuals with access to the internet (% of total pop.)	Positive	International Telecom. Unit
Economic Controls		
Gross National Income per Capita (Current USD)	Positive	World Development Indicators
Consumer Affordability of Electricity (Index)	Negative	RISE
Social Controls		
Secondary enrolment rate (Gross)	Positive	World Bank Data
Framework for stand-alone systems (Index)	Positive	RISE

Table 1 - Summary of Control Variables, Source: Own elaboration

3.2 Data imputation & descriptive statistics

Given the relatively small set of data available, missing values are imputed manually. Imputation is mainly necessary for educational data on secondary gross enrollment rates as here only ~60% of all datapoints were available.

For secondary education, available data for years surrounding those of interest (2011, 2014 & 2017) was used to impute missing year-values. If data for years preceding and following those of interest were available, a linear trend was assumed to impute missing values. The same logic was applied if values were available for three preceding or following years. If just one preceding or following year value was available, all available data was used to derive a sample trend between the available year-value and the missing one (i.e. if 2014 value was missing but 2015 value was available and overall, secondary education increased by 5% across the whole sample from 2014 to 2015, this trend was used to compute the missing 2014 value using the existing 2015 value as a baseline).

For datapoints where no neighboring values were available (education & RISE scores), available datapoints were used to compute the countries relative performance to the whole non-imputed dataset. Assuming that relative performance would remain roughly the same across years of interest, available values for the missing year-value of the non-imputed dataset were then used as a baseline to calculate the missing year-value for said country. In case no data was available, sample or group (HIC, UMIC, LMIC, LIC) averages were used to fill blanks.

All rules used to impute data in this set are outlined in Appendix 1 of this dissertation.

Descriptive Statistics - Non-Imputed Data

Statistic	N	Mean	St. Dev.	Min	Max
Solar PV Capacity (MW)	114	6.0	7.3	0.0	36.8
Account Ownership (%)	98	30.0	19.9	1.5	89.8
- Only Traditional Account (%)	66	17.7	15.1	1.6	84.2
- Only Mobile Account (%)	66	8.7	8.8	-0.000	30.8
Access to Electricity (%)	114	37.5	22.5	4.1	99.4
Access to Internet (%)	114	14.6	13.6	0.0	62.0
GNI per Capita (USD)	110	1,887.6	2,292.7	230.0	11,000.0
Affordability Index	88	65.2	24.9	13.0	100.0
Secondary Education (%)	69	43.4	17.2	9.7	99.9
Stand-Alone System Index	96	39.3	25.8	11.0	100.0

Table 2 - Statistics of Non-Imputed Dataset, Source: Own elaboration

Descriptive Statistics - Imputed Data					
Statistic	N	Mean	St. Dev.	Min	Max
Solar PV Capacity (MW)	114	6.0	7.3	0.0	36.8
Account Ownership (%)	114	30.0	19.6	1.5	89.8
- Only Traditional Account (%)	76	17.3	14.4	1.6	84.2
- Only Mobile Account (%)	76	8.7	8.4	-0.000	30.8
Access to Electricity (%)	114	37.5	22.5	4.1	99.4
Access to Internet (%)	114	14.6	13.6	0.0	62.0
GNI per Capita (USD)	114	1,850.4	2,260.3	230	11,000
Affordability Index	114	64.3	22.5	13	100
Secondary Education (%)	114	44.1	15.7	9.7	99.9
Stand-Alone System Index	114	39.3	24.2	11	100

Table 3 - Statistics of Imputed Dataset, Source: Own elaboration

Tables 2 and 3 provide a summary of the statistics for all variables used in this analysis. Table 2 shows the statistics for the non-imputed dataset and table 3 shows the same statistics after data imputation.

Installed solar PV capacities across the dataset average 6 MW between 2011 and 2017 with no difference before and after imputation as the set is complete. In 2011, average installed capacities are 1.9 MW, rising to 5.6 MW in 2014 and 10.4 MW in 2017. Standard deviation in installed capacities also increase from 3.4 in 2011 to 8.7 in 2017, as averages in some countries remain very low like Zambia at 0.1 MW compared to 37 MW in Kenya in 2017.

Ownership of a bank account at a financial institution or a mobile money provider averages 30% of the total population in both the original and imputed dataset across periods at a standard deviation of 19.9 and 19.6, respectively. This indicates that imputed data pushes observations slightly towards the mean. In 2011, bank account ownership averages 19.6% in the original dataset, rising to 28.8% in 2014 and 41.5% in 2017 with imputation leaving values almost identical. Standard deviation also remains similar after imputation with the original dataset showing values of 15.5, 18.6 and 18.6 for 2011, 2014 and 2017 respectively, compared to 14.8, 17.9 and 19.1 after imputation.

The computed values on ownership of only a traditional bank account at a financial institution average 17.7% and 17.3% in the original and imputed dataset, with standard deviation decreasing slightly from 15.1 to 14.4 after imputation. From 2014 to 2017, averages decrease in the original and imputed datasets from 17.8% and 17.6% to 17.0% and 17.6% respectively. Standard deviation follows, decreasing slightly from 2014 to 2017 in both sets.

Percentages of the population with only a mobile money account stand at 8.7% in both datasets. Standard deviation is a bit higher in the original data at 8.8 compared to 8.4 after imputation. In contrast to traditional bank accounts, values increase from an average of 5.5% (original) and 5.4% (imputed) in 2014 to 12% in 2017 within both datasets. Standard deviation also increases to 8.5 and 8.3 in 2017 compared to 7.6 and 7.1 in 2014. This again highlights how some countries made remarkable developments in mobile banking like Gabon, increasing from close to 4% in 2014 to almost 20% in 2017 compared to countries like Ethiopia, where mobile banking remained at a low of less than 1%.

As for the included technological control variables, access to electricity and the internet increased from 32.8% (electricity) and 6.8% (internet) to 43% and 23.4% respectively. Both indicators display high standard deviations across periods, indicating the large discrepancies between countries in scope.

Economical controls are reflected by GNI per capita and the affordability RISE index. GNI increases from 2011 to 2014 but decreases in 2017, again displaying a high standard deviation. The RISE index rises across periods, also showing a high standard deviation.

Finally, social controls were imputed heaviest in this set with only ~60% of datapoints available for secondary enrollment rates. However, judging from the descriptive statistics imputation does not skew means or standard deviations in general or across time. The sample average was 43% in the original dataset and 44% in the imputed one. Over time, averages increased in both datasets from ~40% to ~45% in 2014 and 47% in 2017. Standard deviation decreases slightly after imputation from around 17 to a little under 16, staying constant over time in both datasets. The second RISE index on stand-alone frameworks generally increased in line with most indicators between 2011 and 2017. Imputation did not alter means or standard deviations substantially with standard deviation remaining high across periods, indicating that an increased mean is driven by a few countries with others lagging behind.

3.3 Estimation problems

Two main issues arise when analyzing the displayed datasets. First, potential endogeneity due to omitted variables and second, errors related to unobserved heterogeneity. Limitations due to the small size of the data available are presented in chapter 4.2.

Endogeneity due to omitted variables arises, when the model does not capture a variable which might be driving both, the dependent and main independent, variables of interest – in this case the growth of solar PV capacities as well as the coverage of bank accounts (mobile & institutional). Given the general complexity of technology diffusion, multiple factors could potentially play that role. As argued by Bawakyillenuo (2012), the diffusion of solar PV in Kenya between the 1960s and 2007 – that is both, on- and off-grid – could be attributed to a set of strong actors promoting the technology. Donor country investment geared towards solar PV as early as the 1960s and 1970s, built the foundation for today's private industry (Bawakyillenou, 2012: 413-414). Another critical success factor for Kenya's successful

PV diffusion was the targeting of an affluent group, namely rich rural households with no grid-connection. Here, even early solar PV appliances could be sold at a profit while recruiting and training technicians on the technology to further develop the market (Bawakyillenuo, 2012: 417). Similar findings can be attributed to the diffusion of mobile money in Africa, where strong actors or individual firms take a leading role in promoting the technology (see e.g. Lashitew, Tulder & Liasse, 2019).

In a more general sense, both the diffusion of (mobile) bank accounts as well as solar PV applications could ultimately be related to a more technologically affluent populace – in terms of education, awareness or income – as well as the general entrepreneurial spirit of an economy. Capturing these factors and their interplay – e.g. how more trained technicians indirectly spread awareness of a technology or how some shops adopting mobile money might send a signal to both customers and the market – is very difficult to capture in a quantitative approach and explains the general preference of in-depth case-studies of research so far.

Another set of indicators which could potentially drive both variables is related to the general infrastructure of a country. Road density, ease of commuting to larger cities, distances to the next "tech shop" or bank etc. could all be influencing a household's decision to invest into a new technology – be it a mobile phone, setting up a (mobile) banking account or purchasing a solar PV application. In this dissertation, access to the internet is chosen as a main indicator on the technological infrastructure of a country, as it is readily available and likely to at least capture some of the effects outlined above.

Another factor to consider is unobserved heterogeneity in our main variables, as data on financial inclusion is only available in three time-periods (2011, 2014 and 2017). Changes in the three years between each period are not reflected anywhere but might be important when assessing causal relations between them. Addressing this issue would only be possible by regressing values for the years of missing observations through some other, available indicator. This would, however, be a questionable approach as no data on any country is available and thus the whole set would be imputed. The much more likely option here is to repeat the approach outlined in chapter 4 of this dissertation, when more surveys on financial inclusion have been conducted.

All these factors need to be considered when discussing the analytical setup of this dissertation as well as the results. And while some can be overcome by modelling techniques, the fact that both, mobile banking and off-grid solar PV appliances, are recent phenomena will only be solved by time.

3.4 Regression model & analytical approach

The main hypothesis of this dissertation is that those countries with a higher coverage of bank accounts (mobile or traditional) also show a higher amount of installed off-grid solar PV capacities. In order to analyze this hypothesis, the following two linear models are used:

1. **Estimating the effect of general bank account coverage (traditional and mobile) on installed off-grid solar PV capacities:**

$$\begin{aligned} Installed\ Solar\ PV\ Capacities_{it} &= \alpha + \beta_1 Accounts_{it} + \beta_2 Electricity_{it} + \beta_3 Internet_{it} + \beta_4 GNI_{it} \\ &+ \beta_5 Affordable_{it} + \beta_6 Education_{it} + \beta_7 StandAlone_{it} + \epsilon_{it} \end{aligned}$$

2. **Comparing the effect of mobile bank accounts and traditional bank accounts on installed off-grid solar PV capacities:**

$$\begin{aligned} Installed\ Solar\ PV\ Capacities_{it} &= \alpha + \beta_1 Traditional\ Accounts_{it} + \beta_2 Mobile\ Accounts_{it} \\ &+ \beta_3 Electricity_{it} + \beta_4 Internet_{it} + \beta_5 GNI_{it} + \beta_6 Affordable_{it} \\ &+ \beta_7 Education_{it} + \beta_8 StandAlone_{it} + \epsilon_{it} \end{aligned}$$

Countries are indicated by **i** and time by **t**. **β** is the indicator-specific factor to measure the impact of each independent variable on the main dependent variables. **Installed Solar PV Capacities** is the main dependent variable, displaying the installed capacity of off-grid solar PV in country i and year t. **Accounts** reflect the percentage of the population using either a mobile or traditional bank account or both in country i and year t. This variable is split into two for the second model, namely **Traditional Accounts**, reflecting the percentage of the population which only uses traditional bank accounts and **Mobile Accounts**, reflecting the percentage of the population using only a mobile bank account. Technological controls are reflected by **Electricity,** indicating the percentage of population with access to electricity, and **Internet** as the percentage of the population with access to the internet. Economical controls are **GNI** as the gross national income per capita and **Affordable** as the RISE Affordability index of electricity. Social Controls are **Education** for gross secondary enrollment rates and **StandAlone** for the RISE index measuring existing frameworks for stand-alone electrification systems.

Instead of a time series regression which might be more common for panel data, this analysis uses individual cross-sectional regressions, where **i** is either 2011, 2014 or 2017 for the respective regression. The main reason to employ cross-sectional regression models is the availability of mobile banking data. Mobile account coverage is only available in 2014 and 2017, making the available panel for this indicator very short. Additionally, initial analyses showed interesting variations in effects of mobile banking coverage between the two available periods. These would be omitted in a panel estimator.

In a first step, model (1) was used without any controls to check for the estimated impact of general bank account coverage on solar PV capacities and to compare the original and imputed datasets for all three time-periods – the results are presented in table 4.

The second step was to introduce controls to model (1) in groups, adding technological controls first, economical controls second and social controls third and check, how coefficients change. This was only done for 2014 and 2017, as the initial step suggests, that there is no effect of bank account coverages on solar PV capacities in 2011 and because data on mobile bank accounts is only available in 2014 and 2017. Results for this step are presented in table 5.

In a final step, bank account coverage was split into the percentage of the population using only traditional bank accounts at a financial institution and those using only a mobile bank account. Again, controls are introduced in the same manner as before to observe changes over time from 2014 to 2017 as well as the interaction between variables. The results are shown in table 6.

4. EMPIRICAL RESULTS & INTERPRETATION

4.1 Presentation of empirical results

All the results presented in this section are computed using R project software. The code can be obtained from Appendix 2 of this dissertation.

	Installed Off-Grid Solar PV Capacities					
	Original Data			Imputed Data		
	2011	2014	2017	2011	2014	2017
	(1)	(2)	(3)	(4)	(5)	(6)
Account ownership	-0.02	0.15***	0.23***	-0.01	0.15***	0.18**
	(0.04)	(0.05)	(0.08)	(0.04)	(0.05)	(0.07)
Constant	2.43**	1.76	1.48	2.04**	1.33	2.83
	(1.03)	(1.74)	(3.55)	(0.94)	(1.64)	(3.20)
Observations	32	33	33	38	38	38
R^2	0.01	0.23	0.21	0.001	0.20	0.16
Adjusted R^2	-0.02	0.20	0.19	-0.03	0.18	0.14
Residual Std. Error	3.60 (df = 30)	5.42 (df = 31)	8.34 (df = 31)	3.47 (df = 36)	5.37 (df = 36)	8.22 (df = 36)
F Statistic	0.35 (df = 1; 30)	9.11*** (df = 1; 31)	8.36*** (df = 1; 31)	0.03 (df = 1; 36)	9.28*** (df = 1; 36)	6.82** (df = 1; 36)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 4 – Results of Model (1) without Controls, Source: Own elaboration

Table 4 displays the results from the first model in order to compare the effect of general bank account coverage on installed solar PV capacities in 2011, 2014 and 2017 between the original and imputed dataset. Regressions 1-3 reflect the original dataset and regressions 4-6 the imputed one.

Three important factors can be observed: First, the original and imputed dataset perform very similarly across years, which warrants the usage of the imputed dataset for further analysis. Second, account coverage does not seem to impact solar PV capacities in 2011 at all. As there is also no data available for mobile banking in 2011, this period is dropped from the analysis. And third, the coefficient of bank account coverage is slightly smaller in 2014 and 2017 in the imputed dataset while losing some significance in 2017 as well. This effect needs to be considered, when interpreting further results.

	Installed Off-Grid Solar PV Capacities					
		2014			2017	
	(1)	(2)	(3)	(4)	(5)	(6)
Account ownership	0.17**	0.18***	0.15**	0.24**	0.24**	0.24**
	(0.07)	(0.06)	(0.07)	(0.09)	(0.09)	(0.11)
Electricity Access	-0.004	-0.03	0.03	0.01	0.01	0.05
	(0.07)	(0.07)	(0.08)	(0.11)	(0.11)	(0.13)
Internet Access	-0.05	-0.06	-0.14	-0.13	-0.17	-0.20
	(0.16)	(0.19)	(0.18)	(0.14)	(0.16)	(0.16)
GNI p.c.		0.0001	0.0003		-0.0001	0.0002
		(0.001)	(0.001)		(0.001)	(0.001)
Affordability Index		0.07*	0.04		0.12	0.11
		(0.04)	(0.04)		(0.08)	(0.08)
Secondary Enrollment			-0.07			-0.11
			(0.09)			(0.13)
Stand-alone System Index			0.12**			0.05
			(0.05)			(0.06)
Constant	1.54	-1.90	-2.04	3.13	-4.24	-3.10
	(1.98)	(2.77)	(3.37)	(3.49)	(5.83)	(7.04)
Observations	38	38	38	38	38	38
R^2	0.21	0.28	0.40	0.19	0.25	0.28
Adjusted R^2	0.14	0.17	0.26	0.12	0.13	0.11
Residual Std. Error	5.50 (df = 34)	5.41 (df = 32)	5.11 (df = 30)	8.30 (df = 34)	8.24 (df = 32)	8.35 (df = 30)
F Statistic	3.02** (df = 3; 34)	2.51* (df = 5; 32)	2.85** (df = 7; 30)	2.67* (df = 3; 34)	2.12* (df = 5; 32)	1.65 (df = 7; 30)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5 – Results of Model (1) with Controls, Source: Own elaboration

Table 5 summarizes the results of introducing different control variables to model (1) in 2014 and 2017. In both periods, bank account coverage remains statistically significant at a minimum of 95% confidence with a very constant coefficient. Coefficients of account ownership in 2014 and 2017 with all controls can be interpreted as follows: A one percent increase in the population with a traditional or mobile bank account reflects an increase in installed off-grid solar PV capacities of 0.15MW in 2014 and 0.24MW in 2017 respectively. A slight decrease is observable in 2014 when introducing the social controls of a stand-alone system index and secondary enrollments. Interestingly, very few controls appear as statistically significant – the only exceptions being the affordability index in 2014 with an unexpected positive impact, as this suggests that those countries with more affordable electricity were more likely to install off-grid solar capacities. The index on frameworks for stand-alone systems also appears as statistically significant, if only in 2014 with an expected positive impact on installed off-grid solar PV capacities.

	Installed Off-Grid Solar PV Capacities					
	2014			2017		
	(1)	(2)	(3)	(4)	(5)	(6)
Traditional Account Only	0.23**	0.28**	0.35***	0.34**	0.38**	0.40*
	(0.10)	(0.11)	(0.10)	(0.15)	(0.18)	(0.21)
Mobile Account Only	0.20	0.18	0.11	0.46**	0.44**	0.44*
	(0.14)	(0.14)	(0.12)	(0.21)	(0.21)	(0.24)
Electricity Access	-0.03	-0.06	0.06	0.01	0.01	0.05
	(0.07)	(0.07)	(0.08)	(0.11)	(0.11)	(0.13)
Internet Access	-0.03	0.01	-0.11	-0.15	-0.16	-0.19
	(0.17)	(0.18)	(0.16)	(0.15)	(0.17)	(0.17)
GNI p.c.		-0.0005	-0.001		-0.0005	-0.0003
		(0.001)	(0.001)		(0.001)	(0.001)
Affordability Index		0.06	0.02		0.12	0.10
		(0.04)	(0.04)		(0.08)	(0.09)
Secondary Enrollment			-0.14*			-0.11
			(0.08)			(0.14)
Stand-alone System Index			0.17***			0.06
			(0.05)			(0.06)
Constant	2.08	-1.40	-1.11	2.31	-4.99	-4.03
	(2.03)	(2.76)	(3.12)	(3.90)	(6.09)	(7.20)
Observations	38	38	38	38	38	38
R^2	0.21	0.28	0.51	0.18	0.24	0.27
Adjusted R^2	0.11	0.15	0.37	0.08	0.09	0.07
Residual Std. Error	5.60 (df = 33)	5.49 (df = 31)	4.71 (df = 29)	8.48 (df = 33)	8.42 (df = 31)	8.53 (df = 29)
F Statistic	2.15* (df = 4; 33)	2.05* (df = 6; 31)	3.71*** (df = 8; 29)	1.82 (df = 4; 33)	1.63 (df = 6; 31)	1.34 (df = 8; 29)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 6 – Results of Model (2), Source: Own elaboration

Table 6 shows the results of model (2), where bank account coverage was split into those parts of a countries population only using traditional bank accounts at a financial institution and those only using a mobile bank account. In 2014, traditional bank account coverage shows a higher impact on installed solar PV capacities compared to general bank account coverage in model (1). This is likely due to the fact, that mobile bank accounts, which were included in general bank account coverage of model (1), are not significantly impacting solar PV capacities in 2014. The traditional account coefficient of 0.35 from regression (3) in table 6 can be interpreted as a 0.35MW increase in installed off-grid solar PV capacities for every percent increase in the population using a traditional bank account. In 2017 however, mobile bank account coverage shows a significant impact on installed solar PV capacities. The impact remains statistically significant when introducing technological and economical controls and is higher than the impact of traditional bank accounts with regression (6) in table 6 displaying a 0.44 MW increase in installed off-grid solar PV capacities for every percent increase in the population using only mobile bank accounts. When introducing social controls, statistical significance decreases from a 95% confidence to 90% for rejecting the null hypothesis.

Contrary to model (1), the affordability index does not show as statistically significant anymore which might indicate a relationship with the main independent variables. The stand-alone system index remains statistically significant with a positive impact. Interestingly, secondary enrolment rates now show statistical significance with an unexpected negative impact, if only in 2014.

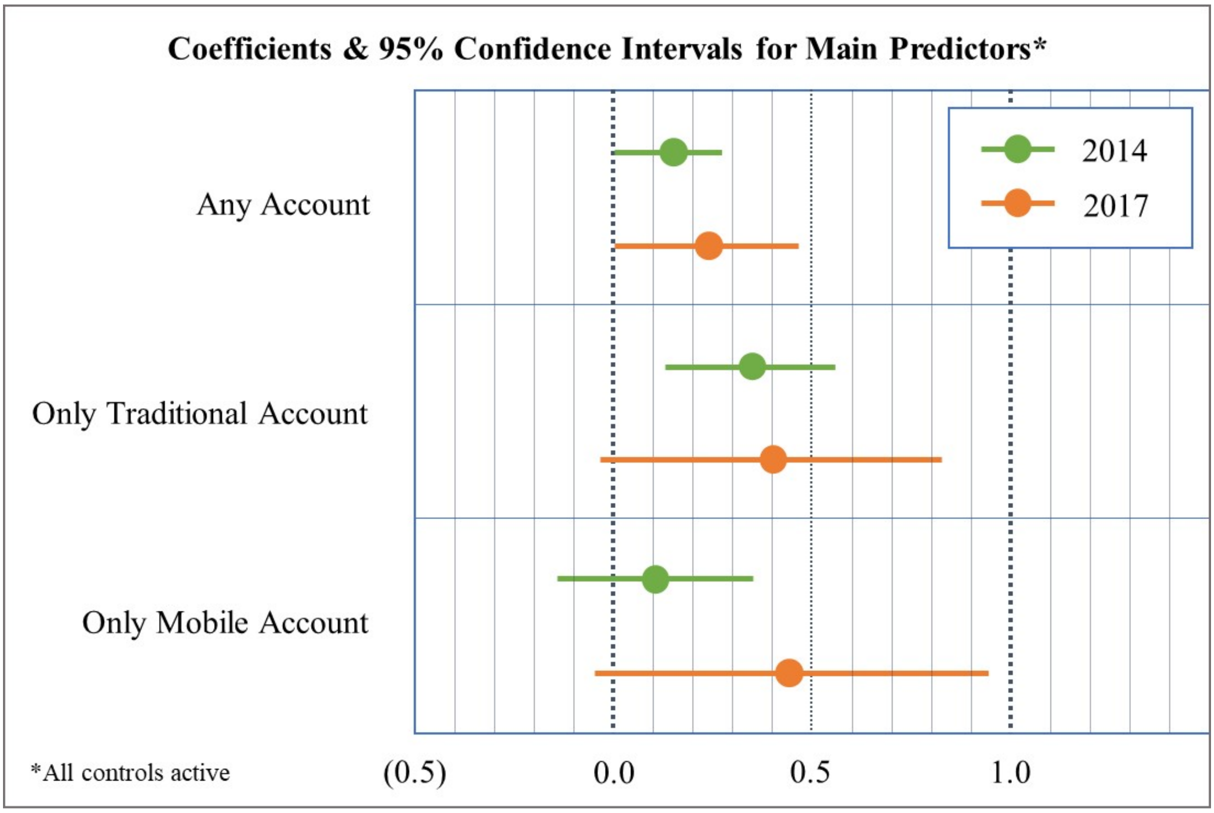


Figure 7 - Summary of coefficients for main predictors incl. 0.95 CI, Source: Own elaboration

Figure 7 summarizes the coefficients and related 95% confidence intervals for the main independent variables of interest with all control variables activated for the respective regression model.

4.2 Interpretation of findings & limitations

The results presented in the last chapter show that in a cross-sectional analysis, access to financial services via bank accounts plays a significant role in advancing off-grid solar PV applications in 2014 and 2017. The fact that bank account coverage does not play a significant role in 2011 could be explained by the early stages in which off-grid solar PV applications still stood in countries of sub-Saharan Africa at that time. In 2011, total installed capacities came up to only 72.5MW in all countries combined. It is possible, that installed capacities up until that point were mainly driven by development projects of international organizations as a way to provide electricity to rural households. Advances of solar PV applications in private markets could explain, why access to finance gained importance by 2014 as households became main customers of producers rather than development agencies.

Mobile bank accounts only became an important driver of solar PV applications in 2017. A missing effect in 2014 could be explained by a variety of factors. First, effects of mobile banking on savings behavior, income or investment decisions might be lagged in their nature. And even though mobile banking applications were already gaining popularity in 2014, on average only 5% of the population in countries of this analysis were using mobile bank accounts exclusively at that time. Effects might therefore either be too small to detect or only took effect in the following years. Another possible explanation could be related to the functionalities offered with mobile banking applications. Take, for example, M-PESA where the initial goal was to provide a large part of the population with person-to-person transactions as well as enabling them to pay bills or receive payments. Functionalities to provide credit, loans or savings accounts were only introduced later (Mas & Radcliffe, 2011: 171). Thus, the provision of services linked to purchasing solar PV applications is likely to take place only at a later stage when (a) a larger share of the population uses mobile bank services and (b) the services provided are geared towards saving and investment decisions of households.

However, the effect of mobile bank accounts and traditional ones is only significant at a 90% confidence level when controlling for education and frameworks for stand-alone systems, which warrants doubt, if that significance would pertain when adding other, potentially more significant controls. It could also point to the fact, that the results are driven by some countries where both traditional account coverage and mobile bank account coverage are individually high as well as installed solar PV capacities. When examining the 95% confidence intervals of coefficients presented in figure 7, there is a likely positive impact of both forms of bank accounts but still, within that interval impacts could also be null or negative.

The RISE affordability index showed a significant effect on installed solar PV capacities in the first regression model in 2014, which decreased in significance when differentiating between traditional and mobile bank accounts and showed in neither model for 2017. This suggests an interaction between the variable for traditional bank accounts only and affordability scores. Interaction could potentially go either way but is likely to be related to the fact that countries with a higher amount of the population using traditional bank accounts should be more developed from an infrastructure perspective and thus more likely to have affordable access to electricity. With the rise of off-grid appliances, that effect is likely to fade as those countries which are less developed in terms of grid-connection and traditional financial access can now supply parts of their population with affordable electricity.

Looking at the RISE index on stand-alone systems, a significant impact prevails for 2014 in both models but does not show for 2017. This indicates the importance of national programs to push the development of systems in earlier stages as well as the impact of financial incentives by public authorities. It eases the market entrance for providers and potentially reduces overall cost for consumers – however, this impact is likely to decrease, once a market has developed which does not need subsidizing from public actors.

Secondary enrollment rates as a measure for education also poses a puzzle on first sight, as it does not show as statistically significant in model 1 for either 2014 or 2017 but does impact solar PV capacities negatively in 2014 when differentiating between traditional and mobile bank accounts. This could again be explained by some unobserved level of technological development, where those countries with a more educated population are more likely to perform better on a general scale of infrastructure and therefore less likely to adapt off-grid technologies in the earlier stages. Another possible explanation could be the targeted population to receive off-grid technologies first. Impact-driven providers of solar PV technology could target those countries which score lower in overall development indicators first in order to provide the ones most in need with electricity. With increases in off-grid electrification generally, that effect could fade as the market develops.

While these results provide some proof of the importance of financial access when electrifying households in sub-Saharan Africa, there are still limitations which need to be considered.

First and foremost, the missing statistical significance of most of the control variables points to a weakness of the model employed as the added controls did not influence solar PV capacities as anticipated. Other controls could have been more appropriate for these models and, if they would also affect mobile bank coverage, could potentially skew the observed coefficients.

That finding leads to the possibility of an omitted explanatory variable which drives both solar PV capacities and bank account coverage, as discussed in chapter 3.3. Theoretically, this problem could be overcome by employing a fixed effects regression in order to filter out time-invariant unobserved differences between the units of analysis instead of a cross-sectional regression. However, given the result that mobile bank account coverage only significance in 2017 and a fixed effects regression would provide the average effect of mobile banking over the two available periods, it is unlikely that an effect would have shown at all. For general bank account coverage, this approach could work with current data availability but would then again limit comparability between traditional and mobile bank accounts.

Finally, the small sample size poses a challenge when generalizing the findings of this dissertation. While statistically significant, the number of observations per time-period was only 38 and thus far from a large N quantitative study to prove causality beyond reasonable doubt. Overcoming this challenge for a cross-country comparison will only be possible when standardized information such as the financial inclusion survey on mobile bank accounts is available for a larger number of years.

5. CONCLUSION

5.1 Recommendations for future research

One of the main challenges to overcome in future research towards this topic is data availability. While the recent nature of both mobile banking accounts as well as solar PV applications explains why data is hardly obtainable before 2010, the frequency of reporting on indicators of financial inclusion does pose a significant hurdle. The financial inclusion database is only updated every 3 years, thus missing important year-by-year variations in mobile bank account coverages which are likely to occur in fast-paced, internet-based business models. Finding alternative sources to estimate the percentage of populations using different kinds of mobile or traditional banking solutions could therefore be crucial to obtain a more nuanced view on the effects on and from these technologies.

More insights are required to unravel factors influencing the diffusion of mobile banking applications and off-grid electrification technologies simultaneously in a cross-country comparison. A sound framework to explain different levels of diffusion for both technologies and their interplay could be crucial to private sector investment as well as policy makers to identify accelerators as well as roadblocks.

With more data available and a stronger framework, the next step in research should be to dissect the effects of financial inclusion on off-grid electrification in different parts of the population. Differentiating between rural households which are most likely excluded from national grids, urban households which might have access but could struggle to afford it as well as the role of richer households investing into future technology would provide important insights on the customer base of solar PV applications and how mobile technologies can help to overcome current problems.

In a more general sense, findings on the causal mechanisms at play between financial inclusion and solar PV diffusion could provide a base for other technologies as well. Water purification systems, sanitary applications or remote educational technology could all enter the private market for households in SSA on a large scale soon, but will face similar problems regarding income, savings and loan accessibility for those households most in need of them. Understanding the financial means required for households and individuals to invest into them is thus already crucial for stakeholders and very likely to increase further in the future.

5.2 Concluding remarks

This dissertation has explored the potential impact of traditional and mobile bank account coverage on installed off-grid solar PV capacities in countries of sub-Saharan Africa. Providing the population of countries in SSA with access to financial services and electricity are key targets of governments as well as the international development community and both have seen a significant increase in the last decade. Despite numerous studies on the individual development and diffusion of mobile banking applications and solar PV technologies in countries of SSA, little research has yet tried to uncover a potential causal link between the two. Finding a positive impact from one to the other offers the chance to streamline resources in the public and private sector to engage in an efficient and effective way of electrifying households through access to financial services.

Results of the analysis show that both, traditional and mobile bank accounts, have a positive, significant impact on installed solar PV capacities. While traditional bank accounts show a significant effect in 2014 and 2017, mobile banking only appears to have made that impact in 2017 but to a higher degree when compared to traditional banking applications. These results support the theory, that mobile bank account coverage is increasing in importance to provide financial services which in turn allows households to invest into technological applications such as solar PV systems.

While limited by data availability and a potential to improve on control variables, these results indicate the need for further research on the impact of financial inclusion on technology diffusion in general and more specifically the technology geared to help alleviate households from poverty.

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APPENDIX

Appendix 1: Rules of Data Imputation

Secondary enrolment rates

1. If data was available for both the preceding and following year, a linear trend between the two years was assumed.
2. If data was available for at least 3 preceding or following years, a linear trend was assumed for the respective following or preceding year.
3. If data was available for one preceding or following year, averages from the non-imputed sample were used to estimate a general trend which was applied to the respective year.
4. If no data was available for either the preceding or following year, but at least two values were available, any existing data in a 10-year span was used to calculate an average performance of the respective country compared with the non-imputed data sample. The non-imputed sample average was then used to estimate the respective missing country-year value
5. If less than 2 values were available at all, averages for the respective year from the non-imputed sample were used.

Total datapoints imputed this way: 45

Account data

1. If any data was available for 2011, 2014 or 2017, the sample average for missing years was used to calculate the countries relative performance, assuming that the country performed the same, relative to the whole sample in years of missing data.

Total datapoints imputed this way: 16

RISE Scores

1. If any data was available for the respective country in 2011, 2014 or 2017, the non-imputed sample average for that year and indicator was used to calculate the countries relative performance, assuming that the country performed the same relative to the whole sample in years of missing data.
2. If no data was available at all for the respective country and indicator, sample averages were used to fill blanks.

Total datapoints imputed this way: 44

GNI

1. Missing datapoints were imputed using the sample average of countries in the same income cluster (LIC, LMIC, UMIC and HIC).

Total datapoints imputed this way: 4

Appendix 2: R Code used for regression models

```
#1. Models from Original Data & Imputed Data for 2011,14 and 17 without Controls

##Original Data first

Model2011AllNoControl <- lm(NonImputed2011$`Solar PV capacities -> IRENA` ~
NonImputed2011$`Account ownership (mobile & fin inst) -> WDI`)

Model2014AllNoControl <- lm(NonImputed2014$`Solar PV capacities -> IRENA` ~
NonImputed2014$`Account ownership (mobile & fin inst) -> WDI`)

Model2017AllNoControl <- lm(NonImputed2017$`Solar PV capacities -> IRENA` ~
NonImputed2017$`Account ownership (mobile & fin inst) -> WDI`)

##Imputed Second

Model2011AllNoControl_Imputed <- lm(Imputed2011$`Solar PV capacities -> IRENA` ~
Imputed2011$`Account ownership (mobile & fin inst) -> WDI`)

Model2014AllNoControl_Imputed <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~
Imputed2014$`Account ownership (mobile & fin inst) -> WDI`)

Model2017AllNoControl_Imputed <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~
Imputed2017$`Account ownership (mobile & fin inst) -> WDI`)

##Summarize Results in Stargazer

stargazer(Model2011AllNoControl, Model2014AllNoControl, Model2017AllNoControl,
Model2011AllNoControl_Imputed,Model2014AllNoControl_Imputed,
Model2017AllNoControl_Imputed, type = "html", digits = 2, out = "ResultsCrossSec1.html",
covariate.labels = c("Account ownership"), column.labels = c("2011", "2014","2017","2011", "2014",
"2017"), model.names = FALSE, dep.var.caption = c("Installed Off-Grid Solar PV Capacities"),
dep.var.labels = c("","Original Data","", "", "Imputed Data", ""))

##2. Continue with imputed data, adding controls in meaningful groups, drop 2011
```

###Technological Controls only

Model2014All_2Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Account ownership (mobile & fin inst) -> WDI` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet`)

Model2017All_2Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Account ownership (mobile & fin inst) -> WDI` + Imputed2017$`Access to electricity` + Imputed2017$`Access to internet`)

###Technological & Economical Controls

Model2014All_4Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Account ownership (mobile & fin inst) -> WDI` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet` + Imputed2014$`GNI per capita` + Imputed2014$Affordability)

Model2017All_4Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Account ownership (mobile & fin inst) -> WDI` + Imputed2017$`Access to electricity` + Imputed2017$`Access to internet` + Imputed2017$`GNI per capita` + Imputed2017$Affordability)

###All Controls

Model2014All_6Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Account ownership (mobile & fin inst) -> WDI` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet` + Imputed2014$`GNI per capita` + Imputed2014$Affordability + Imputed2014$`Sec. Enrolment` + Imputed2014$`Stand-alone systems`)

Model2017All_6Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Account ownership (mobile & fin inst) -> WDI` + Imputed2017$`Access to electricity` + Imputed2017$`Access to internet` + Imputed2017$`GNI per capita` + Imputed2017$Affordability + Imputed2017$`Sec. Enrolment` + Imputed2017$`Stand-alone systems`)

##Combine results in stargazer

stargazer(Model2014All_2Controls, Model2014All_4Controls, Model2014All_6Controls, Model2017All_2Controls, Model2017All_4Controls, Model2017All_6Controls, type = "html", digits = 2, out = "ResultsCrossSec2.html", covariate.labels = c("Account ownership", "Electricity Access", "Internet Access", "GNI p.c.", "Affordability Index", "Secondary Enrollment", "Stand-alone System Index"), column.labels = c("", "2014","","", "2017", ""), model.names = FALSE, dep.var.caption = c("Installed Off-Grid Solar PV Capacities"), dep.var.labels.include = FALSE)

##3. Repeat process from before but differentiate between type of account

```r
##Technological Controls only

Model2014Diff2_2Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Only FIN INST Acc -> Computed` + Imputed2014$`Only Mobile Money Acc -> Computed` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet`)

Model2017Diff2_2Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Only FIN INST Acc -> Computed` + Imputed2017$`Only Mobile Money Acc -> Computed` + Imputed2017$`Access to electricity` + Imputed2017$`Access to internet`)

###Technological & Economical Controls

Model2014Diff2_4Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Only FIN INST Acc -> Computed` + Imputed2014$`Only Mobile Money Acc -> Computed` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet` + Imputed2014$`GNI per capita` + Imputed2014$Affordability)

Model2017Diff2_4Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Only FIN INST Acc -> Computed` + Imputed2017$`Only Mobile Money Acc -> Computed`+ Imputed2017$`Access to electricity` + Imputed2017$`Access to internet` + Imputed2017$`GNI per capita` + Imputed2017$Affordability)


###All Controls

Model2014Diff2_6Controls <- lm(Imputed2014$`Solar PV capacities -> IRENA` ~ Imputed2014$`Only FIN INST Acc -> Computed` + Imputed2014$`Only Mobile Money Acc -> Computed` + Imputed2014$`Access to electricity` + Imputed2014$`Access to internet` + Imputed2014$`GNI per capita` + Imputed2014$Affordability + Imputed2014$`Sec. Enrolment` + Imputed2014$`Stand-alone systems`)

Model2017Diff2_6Controls <- lm(Imputed2017$`Solar PV capacities -> IRENA` ~ Imputed2017$`Only FIN INST Acc -> Computed` + Imputed2017$`Only Mobile Money Acc -> Computed` + Imputed2017$`Access to electricity` + Imputed2017$`Access to internet` + Imputed2017$`GNI per capita` + Imputed2017$Affordability + Imputed2017$`Sec. Enrolment` + Imputed2017$`Stand-alone systems`)

##Combine Results in Stargazer - same layout as before

stargazer(Model2014Diff2_2Controls, Model2014Diff2_4Controls, Model2014Diff2_6Controls, Model2017Diff2_2Controls, Model2017Diff2_4Controls, Model2017Diff2_6Controls, type = "html", digits = 2, out = "ResultsCrossSec4.html", covariate.labels = c("Traditional Account Only", "Mobile
```

Account Only", "Electricity Access", "Internet Access", "GNI p.c.", "Affordability Index", "Secondary Enrollment", "Stand-alone System Index"), column.labels = c("", "2014","","", "2017", ""), model.names = FALSE, dep.var.caption = c("Installed Off-Grid Solar PV Capacities"), dep.var.labels.include = FALSE)

Appendix 3: Data sources used in regression models

Indicator	Data source
Installed solar PV capacities (MW, cumulative)	IRENA - https://www.irena.org/publications/2020/Mar/Renewable-Capacity-Statistics-2020
Account ownership (traditional or mobile, % of population aged 15 or older)	Financial Inclusion Database - https://datacatalog.worldbank.org/dataset/global-financial-inclusion-global-findex-database
Account ownership at a financial institution (% of population aged 15 or older)	Financial Inclusion Database - https://datacatalog.worldbank.org/dataset/global-financial-inclusion-global-findex-database
Account ownership at a mobile money provider (% of population aged 15 or older)	Financial Inclusion Database - https://datacatalog.worldbank.org/dataset/global-financial-inclusion-global-findex-database
Individuals using the internet (% of total population)	International Telecommunication Union - https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
Electricity Access (% of total population)	World Bank Database – Electricity Access - https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?locations=ZG
Gross national income per capita, Atlas method (current USD)	World Bank Database - https://data.worldbank.org/indicator/NY.GNP.PCAP.CD?locations=ZG&name_desc=false
Secondary school enrolment, secondary (% gross):	https://data.worldbank.org/indicator/SE.SEC.ENRR?locations=ZG
RISE scores	https://rise.worldbank.org/scores