Considering the Effects of Mobile Phones on Financial Inclusion in Cambodia

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ABSTRACT This paper examines the effects of mobile phones on financial inclusion in terms of households' uptake of microcredit in Cambodia, with data from the Cambodia Socio-Economic Survey conducted in 2014. The analysis is conducted with a propensity score matching approach to address endogeneity issues of the use of mobile phones and to evaluate the effects. The results suggest that mobile phones are very likely to induce households to take up credit offered by microfinance institutions, in particular for non-agricultural investment purpose, but to discourage households from using credit for non-productive purpose.

Keywords: Mobile phones, financial inclusion, microfinance, Cambodia

Introduction

The recent mobile revolution, combined with technological advancements, has allowed the majority of the world population to call or text messages but also changed the way they live, work and communicate. One of the latest breakthroughs of mobile phones is the possibility for the users to have access to financial information, banking services and implement money transactions through the mobile device, known as mobile financial services. Nevertheless, the thriving development of mobile technology has not fully included people into the financial sector (Maria & Frida, 2014). Half of the adult population in the world is still financially excluded, having limited access to formal bank account (Demirgüc-Kunt & Klapper, 2013). However, approximately 2 billion of 2.5 billion unbanked individuals already possessed mobile phones (Maria & Frida, 2014). Then, with the expansion of mobile phones, the development of mobile financial services and the existing hug financial infrastructure disparity demonstrate a great potential for underserved populations to gain access to formal financial services.

The major barriers to access to formal financial accounts are costs, distances and bureaucracy (World Bank [WB], 2014). These factors are useful to identify market failures and provide policy makers with guidelines on financial policies. Market failure and inadequate polices prevent the poor from gaining access to financial services such as bank account deposit and borrowing etc. Modern information and communication technology (ICT) is very likely to address this market failure, allowing the poor to have access to financial services they need. Increasingly rigorous literature on the evaluation of factors promoting the financial inclusion in the developing world has been paying more attention to the effects of modern ICT such as mobile phones (see, for example, Mihasonirina & Kangni, 2011; William, & Tavneet, 2011; Ahmed, Christoph, Paul, & Ignacio, 2012; Mihasonirina & Kangni, 2012; Maria & Frida, 2014; Shashank 2014). Their findings suggest that mobile phones promote the access to financial services such as bank account deposit and borrowing, then enhancing economic growth. The modern ICT can serve as a tool to develop a platform which helps the developing world to extend the financial services in rural communities, and can help banks reduce the operation as well as transaction costs, increase customer reachability and improve business risk management (Shashank, 2014). Beyond reducing such costs, mobile phones also permit customers to interact more directly with their banks, checking balances and initiating transactions from wherever they are. Using mobile phones as a means to gain access to device offers the customers a level of immediacy, convenience and control that no other channel can provide.

Taking a look at Cambodia, as of 2016, phone market has become saturated, with more than 96% of the Cambodians possessing their phones and over 99% being reachable through some shorts of phone according to Kimchhoy, Lihol and Javier (2016). The authors also found that 13% of the phone users enjoy more than one phone and one in four uses more than one mobile operator. Moreover, approximately 48% of the population owns at least one smartphone and have access to internet or Facebook. Alongside the development of phone market, over these two decades, Cambodia's financial sector has developed rapidly, playing a central role in the economy, in particular from 1997 to 2011 (Bylander, 2015; Seng, 2017). These trends combined with recent financial technology developments and mobile banking have a great potential to promote financial services to be offered to the most vulnerable groups in the Kingdom at a low cost.

To further promote and facilitate mobile phone development and its related financial services in Cambodia, there is a need for more plausible evidence on the wanted effects on financial inclusion. Nevertheless, the earlier literature, discussed above analysed the financial-inclusion-enhancing effects with cross-countries or time series data at the macro levels. The effects may be different by countries because of country-specific heterogeneity and endogeneity issues of the use of mobile phones as well as users' characteristics. These issues may cause the bias and inconsistent estimates of the effects. Moreover, the current paper has an attempt to provide a starting point for the discussion of the relevancy of mobile communications on financial inclusion in Cambodia. The financial inclusion deepened during the period of 2004-2015, from 7% in 2004 to 53% in 2015, along the poverty alleviation from 53% in 2004 to 13% in 2015 (NBC, 2016), very likely suggesting that the deepening of financial inclusion has made a tremendous contribution to reducing poverty in the Kingdom.

The basic objective of the current study is to analyse the effects of mobile phones on financial inclusion in terms of access to microcredit and borrowed amount at the household level in Cambodia, with a particular attention to the issues of sample selection or endogeneity regarding the use of mobile phones. From the econometric point of view, analysing the financial-inclusion-promoting implication of mobile phones at the household level is subject to potential endogeneity due to endogenous bias in the decisions regarding the use of mobile phones. To an extent, this paper accounts for selection bias potentially affecting the differences in outcome variables (credit) between the users and the non-users of mobile phones. Failure to differentiate between the causal effects of use of mobile phones and the impacts of other factors could bring about biased estimates and misleading policy implications. To address these econometric challenges, the study uses a propensity score matching (PSM) method to control for the endogeneity of the decisions concerning the use of mobile phones, which arises from observed confounders. The study concludes that the use of mobile phones promotes financial inclusion in terms of households' access to microloans and borrowed amount. This study contributes to earlier studies by quantifying the effects at the household level and particularly showing that mobile phones promote the uptake of credit for investment in productive activities and reduce the use of credit for non-productive activities.

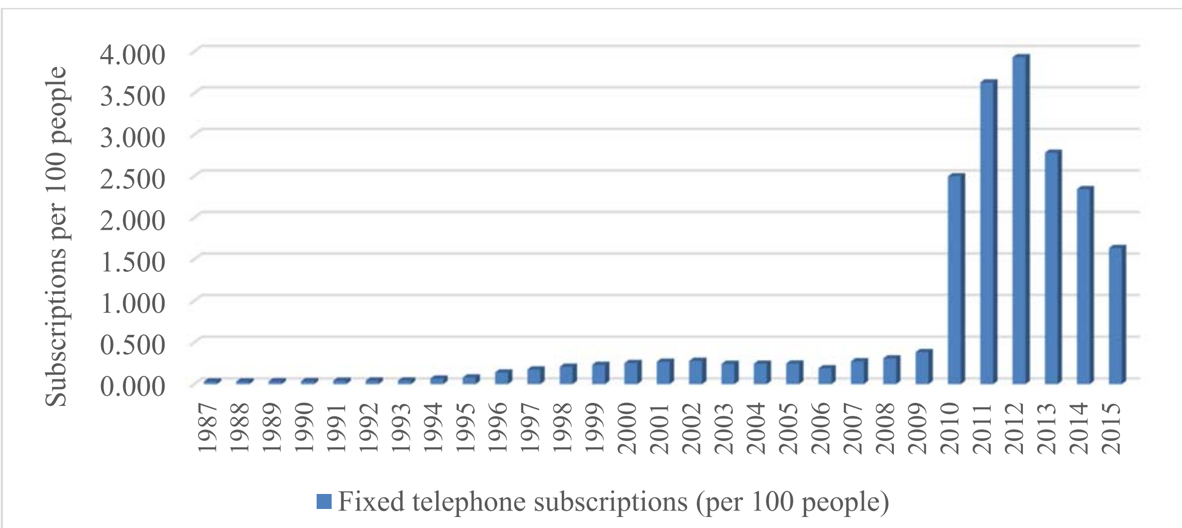
The remainder of this paper is organised as follows. Section 2 describes background of the study. Section 3 reviews main relevant literature. Section 4 describes the empirical analysis approach used in the study. Section 5 discusses the estimated results, and the final section concludes the study.

Background

Fixed telephone subscriptions

Fixed telephone subscriptions refers to the sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones. Figure 1 indicates that fixed telephone subscribers per 100 people from 1987 to 1995 increased in very small number, from 0.03 to 0.08, almost unchanged. Furthermore, from 1996 to 2002, the subscribers increased from 0.14 to 0.28 per 100 people. It is also remarked that the subscribers grew from 2.5 in 2010 to 3.93 in 2012, but later continued declining to 1.64 in 2015. The 2012-2015 declining subscriptions are likely to be resulted from the fact that the subscribers have changed their use of telephones, shifting from using fixed telephones to mobile phones, causing the mobile phones to be in higher demand in Cambodian markets.

Figure 1. Fixed telephone subscriptions per 100 people, 1987 – 2015



Source: World Development Indicator (WDI, 2017)[1]

Diffusion of mobile phone subscriptions

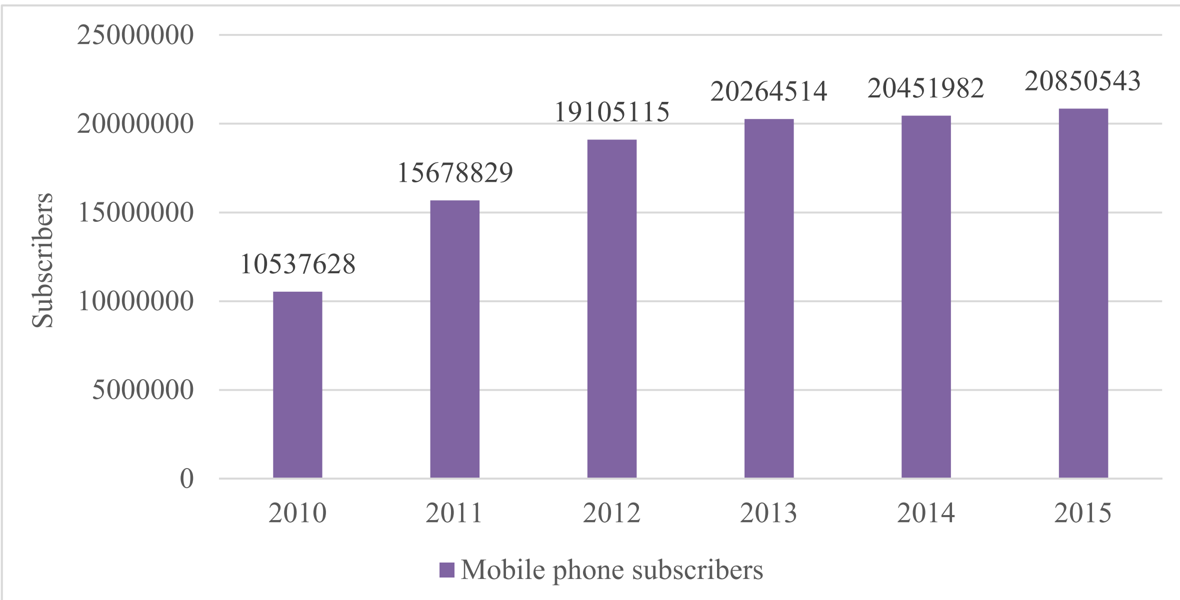
While the fixed telephone subscriptions increased from 2009 to 2012 and had consecutively declining trend from 2012 to 2015, the mobile phone subscriptions had remarkably increasing

[1] Retrieved from http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators# (accessed on June 27, 2017)

trend, with the number of subscribers growing from 10,537,628 in 2010 to 20,850,543 in 2015. These data demonstrate that the mobile phones have become more popular, while the fixed telephones have got less popular.

The mobile phones allow the users to use phone services and even internet services if the phones can be used with internet everywhere they are located. This somehow shows the potential for the mobile phones to promote financial services through allowing the users to have access to financial information such as information on borrowings and reducing transaction costs of financial transaction process. The mobile phones can include many people, the poor in rural communities in particular who own mobile phones, into financial sector.

Figure 2. Mobile phone subscriptions 2010 – 2015



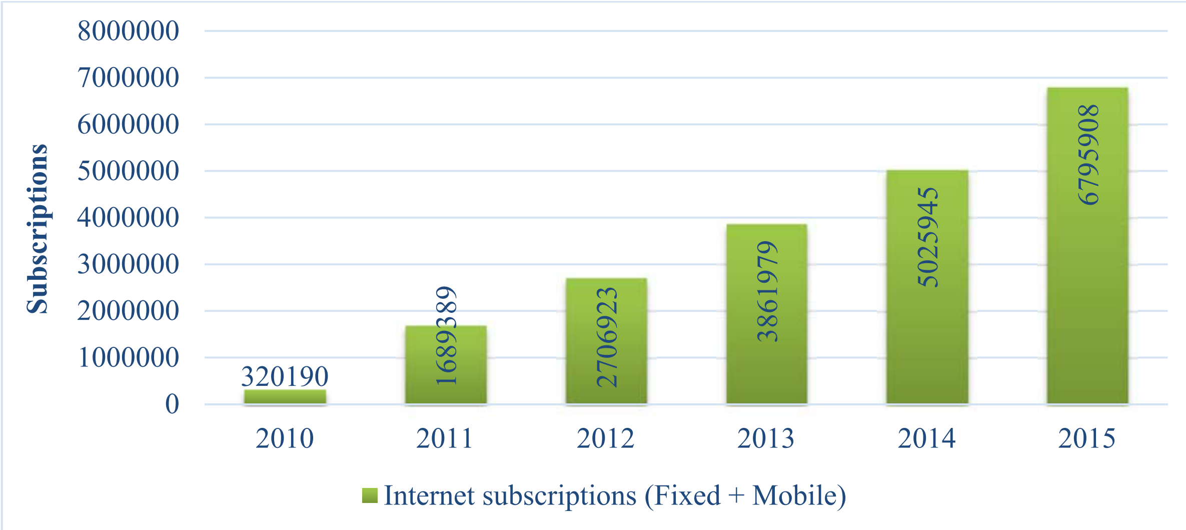
Source: Telecommunication Regulator of Cambodia (2017)

Access to internet

Alongside the increase in mobile phone subscriptions, internet subscriptions have significantly increased. Figure 3 suggests that the internet subscriptions, both fixed and mobile, grew from 320,190 in 2010 to 6,795,908 in 2015. A recent survey shows that approximately 48% of the population is found to have had access to internet or Facebook, with the majority of them having their own Facebook accounts (Kimchhoy, Lihol, & Javier, 2016). In addition, the survey found that the users mostly use smartphones as means to gain access to Facebook, while only approximately 3% of Facebook users employ computers and up to 80% of the users utilise phones to access to internet or Facebook.

These results clearly indicate that the mobile phones are very likely to have main role to play in promoting inclusive financial development in Cambodia. Because the failure of markets, in particular financial markets or credit markets, is in a great part caused by the incomplete information, mobile phones have a great potential to reduce the market imperfection through facilitating the information customers of financial services need to make more efficiently financial decisions.

Figure 3. Internet subscriptions (Fixed + Mobile) 2010 – 2015



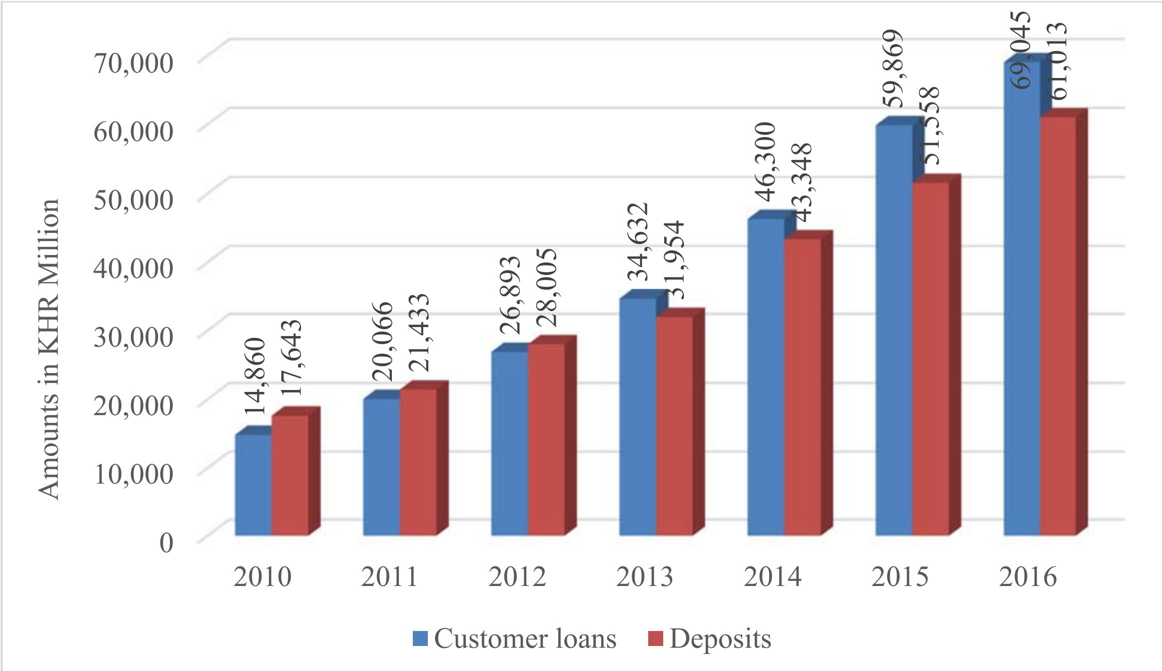
Source: Telecommunication Regulator of Cambodia (2017)

Financial development

Cambodia's financial sector is dominated by banking and microfinance sectors. The banking sector has remarkably developed because of political and macroeconomic stability. By the end of 2016, the total assets grew by approximately 19%, reaching KHR 96 trillion (or USD 23.7 billion); shareholder equity rose by approximately 18%, reaching KHR 17.2 trillion (USD 4.2 billion); borrowing from other sources increased by 65%, reaching KHR 4 trillion (USD 1 million); and deposits grew by 18%, reaching KHR 55.1 trillion (USD 13.9 billion) according to the annual report produced by the National Bank of Cambodia (NBC, 2016). The numbers of depositors and borrowers increased by 14% and 49%, respectively.

The banking development has been making a tremendous contribution to the economic growth and development, through facilitating the financing of investments in economic sectors. Credit provided by banks has a major role in supporting business expansion and domestic demand. Credit was allocated to various economic sectors, with retail receiving 17%, wholesale receiving 15%, agriculture (including also forestry and fisheries) receiving 11%, non-financial services receiving 8%, and construction receiving 8% (NBC, 2016). Many studies, both theoretical and empirical, suggest that financial development contributes to promoting technology, enhancing productivity and then spurring economic growth. This reveals that over these two decades Cambodia's financial sector development had been very likely to improve economic productivities.

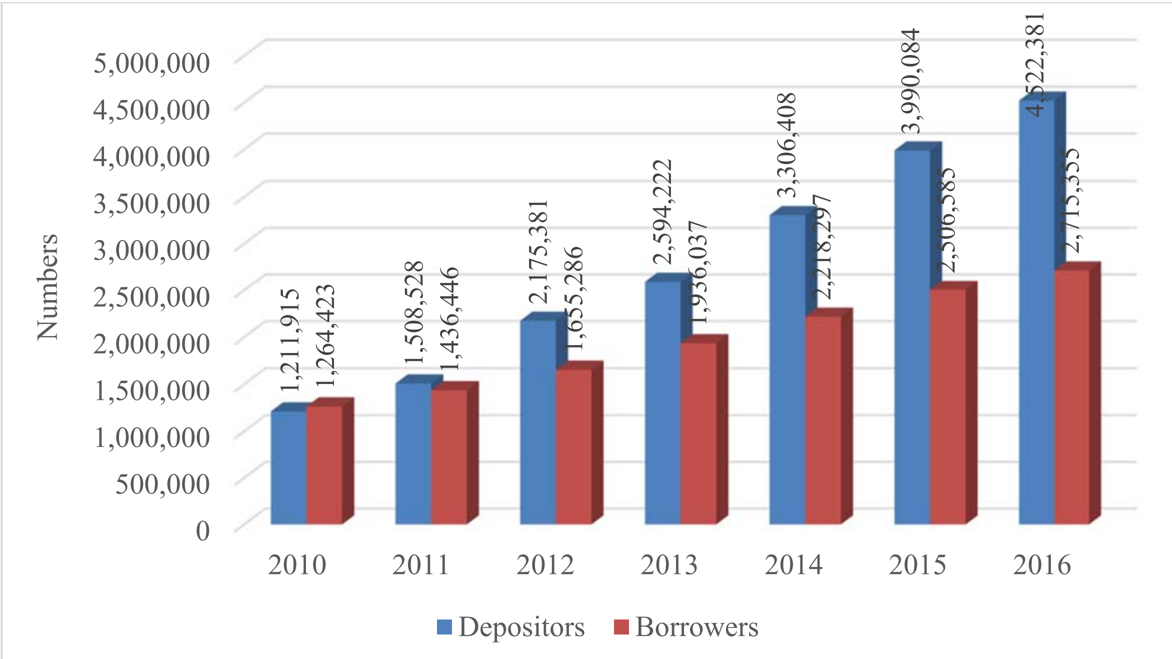
Figure 4. Customer loans and deposits of banks and financial institutions, 2010 – 2016



Source: NBC (2016)

Furthermore, according NBC (2016), as of 2016, the baking system consists of 37 commercial banks, 15 specialised banks, 7 microfinance deposit-taking institutions, 63 MFIs, 170 rural credit operators, 12 leasing companies, 8 third-party processors, 1 credit bureau, 7 foreign-bank representative offices, and 2261 money changers. From 2010 to 2016, the amount of loans and deposits of banks and financial institutions increased significantly; however, the numbers of depositors increased from 1,211,915 in 2010 to 4,522,38 (Figure 4), while the borrowers increased in number from 1,264,423 in 2010 to 2,715,355 (Figure 5). The trend illustrates that from 2013 to 2016, the loan amounts increased faster that the deposit amount; nonetheless, the numbers of depositors increased faster than did the numbers of borrowers. The services offered by banks and financial institutions continue growing through ATM deployment, branches, and representative offices operating in the capital, towns and provinces as well as electronic payment services (NBC, 2016).

Figure 5. Numbers of depositors and borrowers of banks and financial institutions, 2010 – 2016



Source: NBC (2016)

Over the past two decades, Cambodia has experienced remarkably rapid growth of the microfinance sector. From 1997 to 2011, the financial sector, in particular microfinance, had a central role in Cambodia's economy (Bylander, 2015; NBC, 2016; Seng, 2017). Microfinance in Cambodia emerged in the early 1990s from not-for-profit microcredit projects supported by international donors and nongovernmental organisations [NGO], aiming at creating jobs for demobilised soldiers and filling the non-existent banking sector. The sector has evolved over time into more commercial models, in particular since 2000, the year when the sector was dominated by five MFIs providing approximately 175,051 borrowers with an average loan of approximately US$ 137 (Bylander, 2015). Only five years later, the sector has almost doubled in size, with approximately 351,096 borrowers getting the average loan of approximately US$ 143 (Table 1). According to the Cambodian Microfinance Association (CMA, 2014), there were 14 MFIs in 2005, 39 MFIs and 6 NGOs in 2014 operating in the country, offering loans to nearly 1.4 million households. By 2014, the sector has grown with 100,342 reported village offices nationwide (NBC, 2014), approximately 1,779,171 borrowers and US$ 1140 average loan. Table 1 demonstrates in more detail the development of microcredit in the Kingdom from 2005 to 2014.

Table 1. Microcredit growth in Cambodia, 2005 – 2014

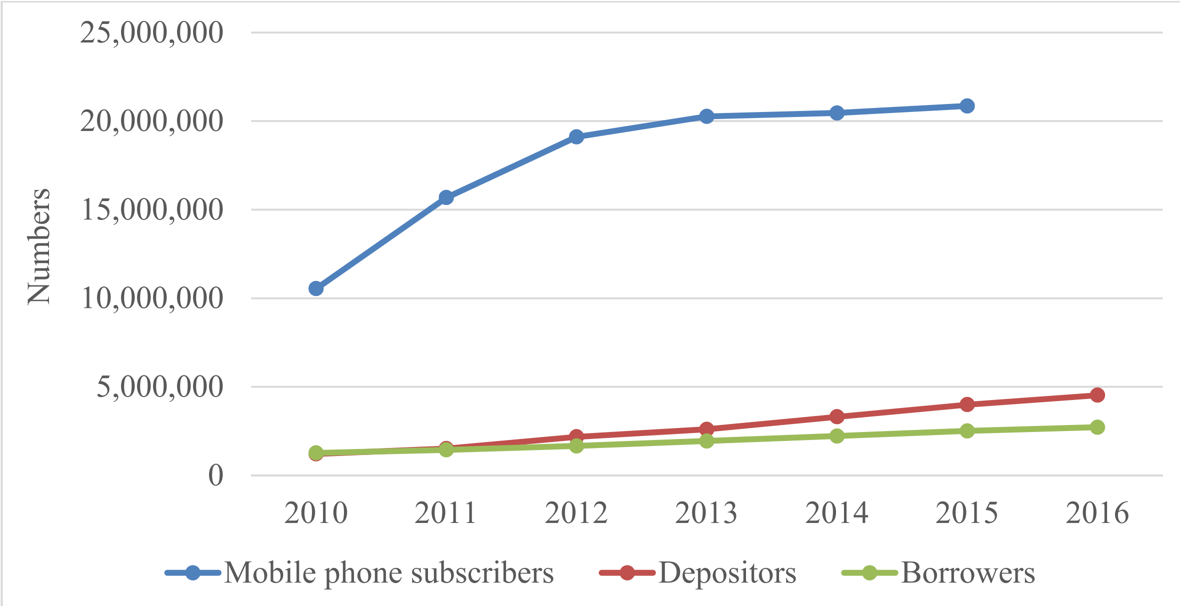
Year	Loan Outstanding (US$ millions)	MFI Borrowers	Average Loan Outstanding (US$)
2005	50.13	351,096	142.78
2006	86.86	446,489	194.54
2007	154.28	601,691	256.41
2008	277.06	825,238	335.73
2009	298.62	871,401	342.69
2010	425.92	992,452	429.16
2011	644.64	1,151,339	559.90
2012	892.66	1,316,265	678.18
2013	1325.2	1,566,526	845.95
2014	2028.56	1,779,171	1140.17

Source: Author's computation from CMA (2014)

Approximately 80% of the formal borrowers live in rural communities, and 81% are women with a repayment rate of 98% before the 2008 financial crisis (CMA, 2014). The MFI microcredit contributes to the expansion of cultivated land area, boosting the agricultural production and rural livelihoods (Eliste & Zorya, 2015). Furthermore, the provision of FMI services was estimated to benefit approximately 3,878,618 Cambodians, or nearly 5 people per household on average (CMA, 2014). This is arguably attributed to the fact that Cambodian low-income households have access to microcredit to run new businesses and/or expand existing ones (Seng, 2017). Furthermore, according to NBC (2016), Microloans offered by MFIs has been oriented to various economic sectors, with agriculture receiving 34%, households receiving 28%, commerce receiving 18%, services receiving 10%, transportation receiving 4%, construction receiving 3%, and others receiving 2%.

At the macro level, during the period of 2010-2016, Figure 6 demonstrates that the numbers of mobile phone subscribers, depositors and borrowers had the same increasing trends. These trends somehow can suggest that the numbers of depositors and borrowers increased along the increased numbers of mobile phone subscribers, more likely revealing the relationship between the former and the latter. That is, it is more likely that mobile phones facilitate the access to financial services such as deposits at and borrowings from banks and financial institutions. However, it is not necessarily to simply conclude that mobile phones enhance financial inclusion in terms of deposits and borrowings. This is because this simple trend investigation does not address the evaluation issues such as endogeneity of the use of mobile phones, which is needed to be controlled for when conducting the assessment. Moreover, the conclusion at macro level can be naïve because such simple trend analysis does not account for the heterogeneity of households using mobile phones.

Figure 6. Numbers of mobile phone subscribers, depositors and borrowers, 2010 – 2016



Source: Author's Compilation from NBC (2016) and WDI (2017)

Furthermore, alongside the increase in mobile phone subscriptions as earlier mentioned and in internet subscriptions (Figures 2, 3 and 6), the numbers of borrowers from MFIs grew significantly. Nevertheless, this does not necessarily mean that the mobile phones promote the access to microcredit due some technical issues such as selection bias and endogeneity of the use of mobile phones. The econometric approach in the next section will address this issues to produce unbiased and consistent estimates of the effects of mobile phones on the access to microcredit in Cambodia by using data at the household level.

Mobile Phones and Financial Inclusion

The review of various related studies shows the importance of the financial inclusion which will act as a win-win situation for both unserved populations and banks. In India, financial inclusion is currently confined to ensure to the access to saving counts; however, it has internationally broader perspective (Shashank, 2014). Financial inclusion could have multiple levels, depending on the level of clients' involvement with financial products and services such as access to credit. Having a current account/savings account on its own cannot be considered as an accurate indicator of financial inclusion (V. Leeladhar, 2006). Technology framework can help the banks to extend their services to underprivileged people, the poor in particular, and at the same time can help them meet their business objectives (Shashank, 2014; NBC, 2016).

The costs, distances and bureaucracy are the major barriers to households' access to formal financial services such as bank accounts and borrowing for income-generating activities (World Bank [WB], 2014). Not only do these factors contribute to banking market failures but also provide policy makers with guidelines on financial policies towards poverty reduction. The market failures and inadequate polices prevent the poor from gaining access to financial services such as bank account deposit and borrowings etc. Modern information and communication technology (ICT) is very likely to address these market failures, allowing the poor to have access to financial services they need.

Increasingly rigorous literature on the evaluation of factors promoting the financial inclusion in the developing world has been paying more attention to the effects of modern ICT such as mobile phones (see, for example, Mihasonirina & Kangni, 2011; William, & Tavneet, 2011; Ahmed et al., 2012; Mihasonirina & Kangni, 2012; Maria & Frida, 2014; Shashank, 2014). Their findings suggest that mobile phones promote the access to financial services such as bank account deposit and borrowings, then enhancing economic growth. The modern ICT can serve as a tool to develop a platform which helps the developing countries extend the financial services in rural communities, and can help banks reduce their operation costs as well as transaction costs, increase customer reachability and improve business risk management (Shashank, 2014). Beyond reducing costs, mobile phones also permit customers to interact more directly with their bank, checking balances and initiating transactions from wherever they are. Moreover, using mobile phones as a tool to gain access to device offers the customers a level of immediacy, convenience and control that no other channel can provide.

Mihasonirina and Kangni (2011) used GMM approach to quantify the effects of mobile phones on economic growth with a sample of African countries from 1988 to 2007. They found that mobile phones promote financial inclusion in terms of borrowing and thus stimulate economic growth. With the same approach, the study by Maria and Frida (2014) comes up with the same conclusion of the financial-inclusion-enhancing effects of mobile phones. In a similar fashion, Andrianaivo and Kpodar (2012) assesses whether mobile phone rollout, in terms of mobile penetration rate as well as the cost of mobile local calls, fosters economic growth in a sample of African countries from 1988 to 2007 through promoting better financial inclusion measured by the number of deposits or loans per head. Using the GMM estimator method to address endogeneity issues, the authors found that mobile phone development contributes significantly to economic growth in African countries through enhancing greater financial inclusion.Moreover, the effects of mobile phones may also have very close linkage with regulatory environment. Peter (2015) analysed the regulatory impacts on mobile money and financial inclusion in African countries – Kenya, Nigeria, Tanzania and Uganda. The author argued that Countries which conduct financial reforms will ultimately be the ones that drive innovation in mobile financial services and build inclusive, secure, and efficient financial sectors.

However, these studies examine the effects using cross-countries data at the macro levels. The effects may be different by countries because of country-specific heterogeneity and endogeneity issues of the use of mobile phones. These issues may cause the bias and inconsistent estimates of the effects. The current paper has an attempt to address these issues in a specific country at the micro level and provide a starting point for the discussion of the relevancy of mobile communications on financial inclusion in Cambodia.

Empirical Analysis

Econometric Approach

Let assume that household i, where i = 1, 2…, N and N denotes the total sample, receives treatment ($M_i = 1$) if using mobile phone, and does not receive ($M_i = 0$) if not using. Let denote T is the subsample of treated households, and C the subsample of controls. The regression equation that defines a model describing the use of mobile phone can be written as follows:

$$M_i^* = \alpha Z_i + v_i \quad (1)$$
$$M_i = \begin{cases} 1, & \text{if household uses mobile phone} \\ 0, & \text{if household does not use} \end{cases}$$

where M_i^* is the probability that household i uses mobile phone (also known as the latent variable). α is the vector of parameters to be estimated, and v is error term under the assumption that $v_i \sim N(0,1)$. Z_i includes household characteristics that can capture household characteristics, head household characteristics, and household assets.

Propensity Score Matching (PSM) Approach

The current study addresses the above mentioned econometric challenges by adopting the PSM approach. Nevertheless, one has to recognize that the PSM has a limitation because it assumes that the selection is based on observed factors; it cannot account for unobserved confounders which affect both the outcome variables and the decision to use mobile phones.[2]

Unlike the instrumental variable (IV) approach, the matching models assume that sample selection bias is eliminated because of conditioning on observed variables (Heckman & Navarro-Lozano, 2004). In the matching models, the conditions of an experiment are created by allowing the users and non-users of mobile phones to be randomly assigned, thus identifying a casual relationship between the decisions of whether to use or not use mobile phone and outcome variables. Let Y_{1i} be the potential outcomes (Table 2) of the treated households ($M_i = 1$) and Y_{0i} be the potential outcomes of the control households ($M_i = 0$). Then, the treatment effects for household i can be defined as:

$$\Delta_i = Y_{1i} - Y_{0i} \quad (2)$$

The parameter that has attracted the most attention in the literature on effect evaluation is the average treatment effects on the treated T (ATT), which is defined as:

$$ATT = E^T(\Delta_i|M_i = 1, Z_i) = E(Y_{1i}|M_i = 1, Z_i) - E(Y_{0i}|M_i = 1, Z_i) \quad (3)$$

where Z_i is a set of observed factors that affect the likelihood of using mobile phones. While, the mean post-treatment outcomes $E(Y_{1i}|M_i = 1, Z_i)$ are observed, the mean counterfactual outcomes $E(Y_{0i}|M_i = 1, Z_i)$ are not. Hence, one needs to choose a proper substitute for $E(Y_{0i}|M_i = 1, Z_i)$ to construct the counterfactual outcomes for estimating the ATT. The only information that can be used is $E(Y_{0i}|M_i = 0, Z_i)$. However, employing the mean outcomes of the untreated households in non-experimental studies is very likely to be subject to the fact that factors determining the treatment decision equally influence the outcome variables of interest, leading to a self-selection bias (Caliendo & Kopeinig, 2008). In this case, the estimate can produce unbiased and consistent ATT if only if

$$E(Y_{0i}|M_i = 1, Z_i) = E(Y_{0i}|M_i = 0, Z_i) \quad (4)$$

To construct both counterfactual outcomes $E(Y_{0i}|M_i = 1, Z_i)$ and $E(Y_{0i}|M_i = 0, Z_i)$, the PSM approach introduced by Rosembaum and Rubin (1983, 1985) is adopted. The PSM is

[2] Alternatively, to address the unobservable selection bias issue, one can adopt the IV approach. However, due to a lack of appropriate identification strategy, the current study cannot purse this approach, i.e. strong and plausible instruments to be employed in the estimation cannot be found in dataset used in the study.

defined as an algorithm matching the treated (users of mobile phone) and untreated households (non-users) based on the conditional probability of using mobile phone (i.e. the propensity score), given the observed characteristics (Essama-Nssah, 2006, p. 5). That is, the PSM constructs a group of statistical comparison by matching every individual observation of users with an observation of non-users with similar characteristics from the non-user group. The propensity score is the probability of using mobile phone $\Pr(M_i = 1|Z_i)$ which will be estimated using either the probit or logit model, specified in Equation (1). The choice of which model is the best is less discussed in the literature when the treatment is binary (Caliendo & Kopeining, 2008). Following the majority of previous studies adopting PSM, the current study uses the logit model to estimate the propensity score.

However, the PSM procedure is valid, relying in part on four fundamental assumptions: (i) conditional independence assumption (CIA), (ii) sufficient region of common support, (iii) participants and nonparticipants from the same data source, and (iv) the access of participants and nonparticipants to the same markets (Heckman, Ichimura, Smith, & Todd, 1998).

(a) Conditional Independence Assumption (CIA)

A possible identification can be provided with the assumption that potential outcomes and treatment assignment are independent given a set of observed variables Z_i which are not influenced by the treatment. Thus, the CIA, unconfoundedness given X_i, can be written as:

$$(Y_{1i}^T, Y_{0i}^C) \perp M_i|Z_i \tag{5}$$

Equation (5) implies that the potential outcomes of treatment and controls are independent of treatment conditional on a set of observed covariates Z_i. That is, the condition for Equation (4) is met ($E(Y_{0i}|M_i = 1, Z_i) = E(Y_{0i}|M_i = 0, Z_i)$). The CIA suggests that given Z_i, the non-users can achieve the same mean outcomes as the users would do if they had not used mobile phone. That is, the selection is only determined by observed factors, and all covariates affecting the use of mobile phone and potential outcomes are simultaneously observable to researchers.

(b) Common Support or Overlap Condition

The second fundamental assumption is the sufficient region of common support or overlap condition, which requires that the propensity score be strictly between zero and one. That is,

$$0 < P(M_i = 1|Z_i) < 1 \tag{6}$$

Equation (8) requires that the probability of being users and non-users for households with similar characteristics X_i be strictly positive. Under the overlap condition, observations of the treatment have comparison observations nearby in the distribution of propensity score (Rosenbaum & Rubin, 1983; Heckman et al., 1998). This suggests that the effectiveness of PSM is also dependent on a large and approximately equal number of treated and untreated households so that the common support area can be sufficiently substantial. In general, there are two common approaches to determining the common support region. The first approach is based on a comparison between the minima and maxima of the score in both groups. The basic criterion is to eliminate all observations whose propensity score is higher than the maximum and lower than the minimum in the opposite group (Caliendo & Kopeinig, 2008). The second one is based on an estimation of the density distribution in both groups and uses a trimming method to determine the region of common support (Smith & Todd, 2005). If Equations (5) and (6) are valid, the PSM method is a plausible approach to estimating unbiased and consistent ATT (Asfaw, Lipper, Dalton, & Audi, 2012).

Nevertheless, conditioning on covariates Z_i could cause "a curse of dimensionality" if vector X_i has a high dimension (Rosenbaum & Rubin, 1983). For example, if Z_i has k dichotomous covariates, the number of potential matches will be equal to 2^k. To address this problem, Rosenbaum and Rubin (1983) suggest conditioning the matching on the propensity score in lieu of the covariates, by proving that the potential outcomes are equally independent of treatment conditional upon the propensity score if (they are) independent of treatment conditional upon covariates Z_i. Then, the first condition expressed in Equations (5) and (6) can be rewritten as unconfoundedness given the propensity score and common support conditional on the score as follows:

$$(Y_{1i}^T, Y_{0i}^C) \perp M_i | P(Z_i) \quad (7)$$

$$0 < P(M_i = 1 | P(Z_i)) < 1 \quad (8)$$

(c) Estimation of Effects

Given that the CIA assumption is satisfied and there is overlap between the user and non-user groups, strong ignorability is constituted (Rosenbaum & Rubin, 1983). Then, the PSM estimator for unbiased and consistent ATT given by Equation (3) under the condition given by Equation (4) can be rewritten as:

$$ATT = E^T(\Delta_i | M_i = 1, P(Z_i)) = E(Y_{1i} | M_i = 1, P(Z_i)) - E(Y_{0i} | M_i = 1, P(Z_i)) \quad (9)$$

and

$$E(Y_{0i} | M_i = 1, P(Z_i)) = E(Y_{0i} | M_i = 0, P(Z_i)) \quad (10)$$

Equation (9) suggests that the PSM estimator for ATT is a mean difference in outcomes within the common support region, weighted by the propensity score distribution of market participants. Hence, following Dehejia and Wahba (2002), the PSM estimator for ATT expressed by Equation (9) can be rewritten in general as:

$$ATT = E^T(\Delta_i | M_i = 1, P(X_i)) = \frac{1}{T}\sum_{i=1}^{T}\left[Y_{1i} - \sum_{j=1}^{C} W(i,j) Y_{0ij}\right] \quad (11)$$

where T is the total number of treated households (users), while C is the total number of control households (non-users). Y_{1i} is the post-treated outcomes of treated household i, while Y_{0ij} is the outcomes of j^{th} control household that matches the i^{th} treated household. $W(i,j)$ is a weight function with positive value. The further discussion on the implementation of PSM is presented in Appendix A1.

Data

The current study uses the data from the CSES carried out in 2014 by the National Institute of Statistics (NIS) for the empirical analysis. In the 2014 CSES, a total of 12,096 households within 25 provinces (all provinces in Cambodia) were selected as the sample, which is the largest sample size among the CSESs. Although the NIS has conducted the CSES annually since 2007, the 2014 dataset is the most updated and represents the nationwide sample of the household survey. Nevertheless, some households did not provide full information on the variables of interest, thus there are missing observations. Adjusting for missing observations, the final sample count is 7801 households in the regression analysis.

Variables Used in the Analysis

The dependent variables in the outcome equations capturing the financial inclusion include formal borrowing, formal productive borrowing, agricultural borrowing, non-agricultural borrowing, borrowing for consumption expenditure, borrowing for other non-productive expenditure, and borrowed amount.

Table 2. Summary of variables

Variables	Definition
Dependent	
- Mobile phone	=1 if the household uses mobile phone(s)
- Formal borrowing	=1 if the household takes up microcredit from MFIs and/or NGOs
- Formal productive borrowing	=1 if the household takes up microcredit from MFIs and/or NGOs for income-generating activities
- Agricultural borrowing	=1 if the household takes up formal microcredit for investment in agricultural activities
- Non-agricultural borrowing	=1 if the household takes up formal microcredit for investment in non-agricultural activities
- Consumption borrowing	=1 if the household takes up formal microcredit for household consumption expenditure
- Other non-productive borrowing	=1 if the household takes up formal microcredit for other non-productive activities such as to buy motorbike, to repay debt etc.
- Borrowed amount	The amount the household borrowed in Riel from MFIs and/or NGOs
Independent	
- Household head's age	Natural log of household head's age
- Household head's gender	=1 if the household is female-headed
- Primary education	=1 if the household head completed primary education
- Secondary education	=1 if the household head completed secondary education
- Higher education	=1 if the household head completed higher education
- Household head's ethnicity	=1 if the household head is Khmer
- Farmer	=1 if the household head is farmer
- Agricultural wage worker	=1 if the household head is agricultural wage-paid worker
- Non-agricultural wage worker	=1 if the household head is non-agricultural wage-paid worker
- Professional	=1 if the household head is professional
- Other career	=1 if the household head is not in these occupational categories
- Household members < 15	Total household members under the age of 15 years
- Household members > 64	Total household members over the age of 64 years
- Working-age household members	Total household members of 15 – 64 years of age
- Landholding	Natural log of landholding in hectares owned by the household

The dependent variables used in the treatment equation is a binary variable for the use of mobile phone. The explanatory variables in the treatment equation consist of household head's characteristics, household characteristics and household assets. Household head's characteristics include age, gender and ethnicity. The heads are also grouped into four categories according the educational levels – primary education, secondary education, and higher education. The heads' occupations are similarly categorised into five groups – farmer, agricultural wage worker, non-agricultural wage worker, professional (including lawyer, teacher, doctor, and other salary-paid employees), and other career (armed force, student, unemployed, retired person etc.). Household characteristics consist of household members under the age of 15 years, household members over the age of 64 years and working-age household members. Household members under the age of 15 years and over the age of 64 years are included in the models to capture the impacts of dependents on the households' use of mobile phones. The variable of working-age members is used to control for the effects of active household members on the utilisation of mobile phones.

Landholding in hectares is included in the model to capture the effects of household endowment on the decision to use mobile phones. The landholding variable has a low potential for endogeneity (Seng, 2015) because the sampled households in the current study represent the households in rural Cambodia where land markets are inactive (Azam et al., 2012; Seng, 2017). However, it is difficult to hypothesise about the effects of these explanatory variables' effects on the use of mobile phones because there is no conventional guidance on the determinants of household decision to use mobile phones. The definition of all variables are summarised in Table 2.

Results and Discussion

This section starts with a description of summary statistics of main variables used in the analysis and a descriptive statistical analysis of the differences between farmers who work off the farm and those who do not. The section ends by presenting econometric analysis results.

Descriptive Statistics

Table 3 presents general differences between the users of mobile phones and non-users in terms of the variables of interest. The summary statistics reported in Table 3 illustrate some remarkable differences between the users and the non-users in terms of each variable, which are supported by simple statistical tests of differences in means, in particular the variables capturing the financial inclusion. For example, with an average of approximately 17%, the users' borrowing from the formal lenders is significantly lower than the non-users' formal borrowing, with an average of approximately 19%. In a similar fashion, the users' borrowing for agricultural investment, household consumption expenditure and for other non-income-generating activities is significantly lower than the non-users' borrowing for these activities.

In contrast, with an average of approximately 5%, the users' borrowing for non-agricultural investment is significantly higher that the non-users' borrowing for this investment, with an average of approximately 3%. Furthermore, the users' borrowed amount of 4,203,060 Riels (US$ 1025) is significantly higher than the non-users' borrowed amount of approximately 1,407,796 Riels (US$ 343).[3] Nevertheless, these results do not necessarily suggest that using mobile phones decreases or increases the household borrowing due to such issues as the endogeneity of the decision to use mobile phones, which arises from selection bias and household heterogeneity (see, for example, Seng, 2017). Further detail on the data on the differences between the users of mobile phones and non-users in terms of other variables of interest is reported in Table 3.

[3] The amount is converted into US dollar at the exchange rate of 1 USD = 4100 riels.

Table 3. Household characteristics by users and non-users of mobile phones

Variables	Users		Non-users		Difference in Mean
	Mean	SD	Mean	SD	
Formal borrowing	0.172	0.378	0.185	0.388	-0.013*
Formal productive borrowing	0.078	0.269	0.078	0.268	0.001
Agricultural borrowing	0.086	0.280	0.117	0.321	-0.031***
Non-agricultural borrowing	0.053	0.225	0.026	0.160	0.027***
Borrowing for consumption	0.111	0.314	0.176	0.381	-0.065***
Other non-productive use borrowing	0.081	0.274	0.105	0.307	-0.024***
Formal borrowed amount	4,203,060	9,993,676	1,407,796	3,299,428	795,264***
Household head's age	46.242	12.715	44.952	15.055	1.291***
Household head's gender	0.175	0.380	0.250	0.433	-0.074***
Primary education	0.403	0.491	0.476	0.499	-0.073***
Secondary education	0.422	0.494	0.185	0.388	0.237***
Higher education	0.031	0.173	0.007	0.086	0.024***
Household head's ethnicity	0.962	0.191	0.957	0.202	0.005
Farmer	0.409	0.492	0.716	0.451	-0.307***
Agricultural wage worker	0.016	0.126	0.068	0.252	-0.052***
Non-agricultural wage worker	0.206	0.405	0.042	0.201	0.164***
Professional	0.114	0.318	0.018	0.134	0.096***
Other career	0.020	0.141	0.019	0.137	0.001
Household members < 15	1.454	1.215	1.588	1.341	-0.135***
Household members > 64	0.185	0.464	0.234	0.511	-0.050***
Working-age household members	3.437	1.640	2.701	1.380	0.736***
Landholding	2.257	10.536	1.449	4.692	0.808***

Notes: The borrowed amount is in riels (Cambodian currency).
* denotes test statistic significance at 10% level.
*** denotes test statistic significance at 1% level

Determinants of Households' Utilisation of Mobile Phones

The propensity of using mobile phones is estimated by using the logit model; and the estimated results are reported in Table 4. The estimated results suggest that the likelihood of using mobile phones are negatively and significantly determined by household head's gender (female), household head's occupations (farmer, agricultural worker) and the household numbers under 15 years of age. That is, it is very likely that households headed by persons who have these characteristics have lower probabilities to use mobile phones. Nevertheless, the probability of using mobile phones is positively and significantly determined by the heads' education status (primary and secondary education), some occupations (non-agricultural worker and professional) and some household characteristics (working-age household members). These characteristics are very likely to induce the households to use mobile phones because of their job characteristics require more communication in the society than other occupations status such as farmers and agricultural workers and so forth. Furthermore, household assets captured by landholding in hectare has significantly positive correlation with the likelihood of using mobile phones, revealing that household endowments are very likely to encourage the decision to use mobile phones.

Table 4. Determinants of household use of mobile phones (logit model)

Variables	Coef.	SE	*P*-value
Household head's age	10.957***	3.192	0.001
Household head's age squared	-1.467***	0.432	0.001
Household head's gender	-0.200*	0.110	0.070
Primary education	0.615***	0.101	0.000
Secondary education	1.197***	0.116	0.000
Higher education	0.156	0.409	0.703
Household head's ethnicity	-0.211	0.224	0.346
Farmer	-1.019***	0.142	0.000
Agricultural wage worker	-1.578***	0.382	0.000
Non-agricultural wage worker	0.777***	0.254	0.002
Professional	0.690**	0.287	0.016
Other career	-0.316	0.440	0.472
Household members < 15	-0.079**	0.032	0.013
Household members > 64	0.040	0.103	0.696
Working-age household members	0.258***	0.030	0.000
Landholding	0.134***	0.036	0.000
Constant	-21.144***	5.835	0.000
Observation	3496		
Prob > chi2			0.000
Pseudo-R^2	0.113		
Log likelihood	-2022.744		

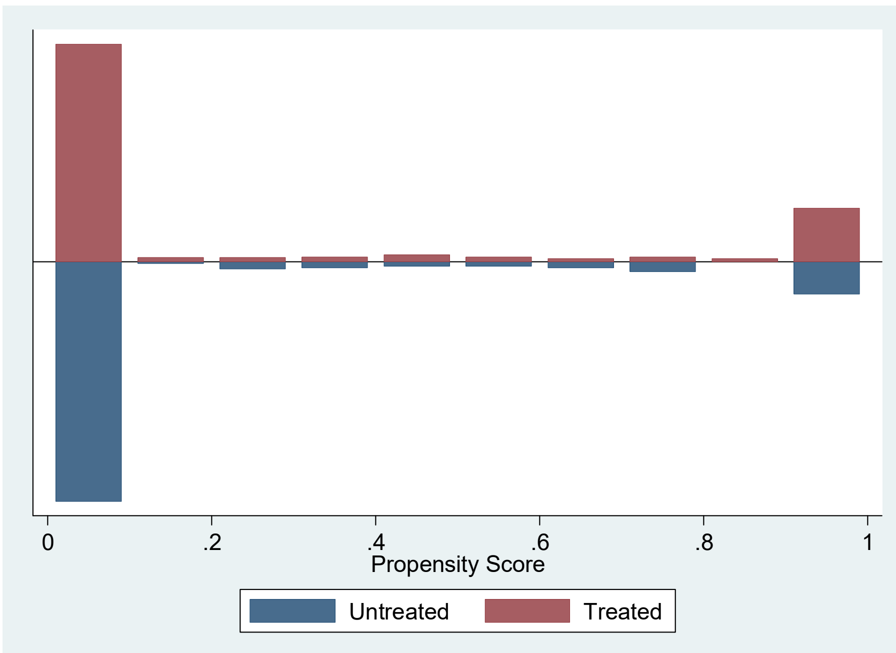
* denotes test statistic significance at 10% level.
** denotes test statistic significance at 5% level.
*** denotes test statistic significance at 1% level.

Effects of Mobile Phone Utilisation on Uptake of Credit

The interest is in the underlying causal effects of mobile phones on financial inclusion in terms of borrowing from MFIs – formal borrowing, formal productive borrowing, agricultural borrowing, non-agricultural borrowing, borrowing for consumption expenditure, borrowing for other non-productive expenditure, and borrowed amount. The analysis break the borrowing by borrowing purpose to examine the effects of mobile phones on borrowing for productive and non-productive purposes. The simple mean comparisons between the users and non-users illustrates the significant differences in terms of these outcome indicators, except the formal productive borrowing. The problem with this mean comparison tests is non-comparability of the two sub-samples and also the fact that they do not control for the effects of other covariates determining the use of mobile phones (Asfaw et al., 2012), producing bias and inconsistent estimates of the effects.

The PSM approach is used to address this issue and to verify whether these differences remain unchanged after accounting for all observed confounders. Before turning to evaluating the effects of mobile phones on financial inclusion, the quality of matching process is briefly discussed. After matching the propensity score for user and non-user groups, it is important to check the common support condition.[4] Figure 4 presenting the density distribution of the estimated propensity scores for the two groups demonstrates that the common support condition is satisfied, with substantial overlap in the distributions of the propensity scores of both user and non-user groups. The bottom half of the graph presents the propensity score distribution for the nun-users, while the upper half shows the users. The densities of the scores are on the y-axis.

Figure 4. Common support region



Of note, a main objective of the propensity score estimation is to balance the distribution of related covariates between the users and non-users, rather than to obtain a prediction of the selection treated. Table 5 presents in detail the results of covariate balancing tests before and after matching.[5] For the KM method, the difference in standardized mean for all observed covariates employed in the score decreases from approximately 18% before matching to approximately 2% after matching. Similarly, for the NNM method, the difference in standardized mean for all observed covariates employed in the propensity score is reduced from approximately 18% before matching to approximately 9% after matching. In addition, in the appendix, the differences in standardized means for individual covariates used in the propensity score estimation are also reported in Table A1 and Table A2 for the KM method and NNM method, respectively.

[4] This paper implements the common support region, following the example of Leuven and Sianesi (2003), discarding observation from the user group, whose propensity score is higher than the maximum or less than the minimum propensity score of non-users.

[5] The common support graph, covariate balancing test and ATT results are obtained using the Stata 11 pstest and psmatch2 commands, respectively (Leuven & Sianesi, 2003).

These results reveal that there is a substantial reduction in total bias through matching; however, the KM method is more plausible in terms of bias reduction and variance after matching. For both matching methods, the pseudo-R^2 is significantly reduced, from approximately 11.3% before matching to approximately 0.1% and 2.5% for the KM and NNM methods, respectively after matching. However, the p-value of likelihood ratio tests of the joint significance of the covariates are nonsignificant after matching, while they are significant before matching, only for both methods. The low mean standardized bias, low pseudo-R^2 and the nonsignificant p-values after matching demonstrate that the KM method's balancing property is more satisfied than the NNM method's balancing property, thus the specification of the propensity score is more plausible for the KM method than for the NNM method.

Table 5. Matching quality before and after matching

	Pseudo-R^2 before matching	Pseudo-R^2 after matching	$p > \chi^2$ before matching	$p > \chi^2$ after matching	Mean bias before matching	Mean bias after matching	Var. before matching	Var. after matching
KM	0.113	0.001	0.000 (513.95)	1.000 (3.05)	17.8	1.7	81	31
NNM	0.113	0.025	0.000 (513.95)	0.277 (17.73)	17.8	9.1	81	44

Notes: Likelihood ratios are in parentheses. Mean bias is the mean standardized bias.

The estimated results of the effects of mobile phones on financial inclusion based on the two matching algorithms, KM and NNM, are reported in Table 6. Similar to Clément (2011), the current study uses a generalized NNM, the nearest five-neighbor matching approach, which takes the average outcomes of the nearest five comparison units as the counterfactual for individual treated units. Alternatively, the study also estimates the ATT using the KM with Gaussian type (normal) and bandwidth parameter fixed at 0.06, following Clément (2011), in part, to check the robustness.

The estimated ATT results from the KM method suggest that by controlling for observed confounding factors that can lead to the endogeneity of the decisions regarding the use of mobile phones, the percentage of the mobile phone users taking up credit from MFIs, with approximately 54%, is significantly higher than that of the non-users, with approximately 47%. This result reveals that mobile phones are very likely to facilitate the access to formal credit. By separating the borrowing for productive purpose (agricultural and non-agricultural investments) to examine the effects of mobile phones on household access to credit for income-generating purpose, the percentage of the users, with approximately 27%, is significantly higher than that of the non-users, with approximately 21%. Furthermore, by breaking the credit for productive activities into agricultural and non-agricultural activities, the mobile phones are more likely to promote the credit for non-agricultural investment, with the users being 12% significantly higher than the non-users that account for only 6%. This result clearly shows that mobile phones are very likely to promote the use of credit for income-generating activities, in particular the use of credit for non-agricultural investment.

Nonetheless, for the borrowing for non-productive activities such as for consumption expenditure and dwelling purchase, the mobile phones are more likely to reduce such a borrowing. For example, the percentage of users borrowing for consumption expenditure, with approximately 31%, is significantly lower than that of the non-users, with approximately 38%.

As far as the borrowed amount is concerned, with approximately 3,544,364 riels (US$ 864), the users' borrowed amount is significantly larger than that of the non-users, with approximately 1,639,975 riels (US$ 400). These results are consistent with the previous studies at the macro level (see, for example, Shashank, 2014; Mihasonirina & Kangni, 2011; Maria & Frida, 2014).

Table 6. Effects of mobile phones on the uptake of credit

PSM Methods	Outcome Variables	Outcome Means		Difference (ATT)	Std. Err.	*t*-Statistic
		Users	Non-users			
KM						
	Formal borrowing	0.54	0.47	0.07***	0.02	3.32
	Formal productive borrowing	0.27	0.21	0.06***	0.02	3.26
	Agricultural borrowing	0.35	0.33	0.02	0.02	0.98
	Non-agricultural borrowing	0.12	0.06	0.06***	0.01	5.36
	Borrowing for consumption	0.31	0.38	-0.07***	0.02	-3.17
	Other non-productive credit use	0.24	0.26	-0.02	0.02	-0.84
	Formal borrowed amount	3,544,364	1,639,974.9	1,904,389.09***	265,045.71	7.19
NNM						
	Formal borrowing	0.55	0.52	0.03	0.05	0.63
	Formal productive borrowing	0.29	0.21	0.08	0.04	1.86
	Agricultural borrowing	0.35	0.30	0.05	0.05	1.03
	Non-agricultural borrowing	0.13	0.05	0.08**	0.03	2.92
	Borrowing for consumption	0.32	0.41	-0.09	0.05	-1.86
	Other non-productive credit use	0.22	0.26	-0.04	0.04	-0.84
	Formal borrowed amount	4,348,098	2,745,061.4	1,603,036.6	870,956.75	1.84

** denotes test statistic significance at 5% level.
*** denotes test statistic significance at 1% level.

The ATT results from the NNM method suggest that, although other outcome variables are nonsignificant, the signs of the ATT related to each variables are consistent with the results from the KM method. These results somewhat indicate the robustness of the estimation of the effects. Of note, the mobile phones are still very likely to promote the use of credit for non-agricultural investment. Nevertheless, as mentioned earlier, the ATT estimated results from the KM method are more satisfactory than those from the NNM method. This result makes a contribution to earlier studies that found in general that mobile phones promote access to credit at the macro level (see, for example, Mihasonirina & Kangni, 2011; Mihasonirina & Kangni, 2012; Shashank, 2014; Maria & Frida, 2014).

The fact that the mobile phones can promote the uptake of credit for income-generating activities is very likely be attributed to their transaction-costs-reducing effects. Using mobile phones allows the users to have easier access to a large amount of information, in particular on the process of applying for credit and financial knowledge through by-phone communication, then reducing business risk. With such information, the users are induced to take out credit to undertake investments in income-generating activities, especially in non-agricultural investment.

The sensitivity of matching estimates to unobserved confounders is also analysed following Clémont (2011) and Aakvik (2001) by using Rosenbaum bound approach.[6] The results are reported in Table A3 in the appendix corresponding to the KM method.

As discussed in earlier Section, the Rosenbaum bound approach that uses the matching estimates to compute confidence intervals of the treatment effect with different Γ values is adopted to conduct the sensitivity test.

Table A3 shows that the estimated effects of mobile phone usage on variables measuring financial inclusion, except for the formal borrowing, are very likely to be sensitive to hidden bias arising from unobserved factors. For the the likely-hidden-bias estimation of the effects corresponding to those variables, the lowest Γ value producing a 95% interval of confidence that encompasses zero is 1.5, meaning that individual households with the same covariates differ in the odds of mobile phone usage by a factor of 50%. This result suggests that the estimated effects of mobile phone use are sensitive to hidden bias due to unobserved confounders. This sensitivity issue may be because of the inclusion of some variables that influence simultaneously the use of mobile phones and outcome variables, except for the formal borrowing. Moreover, the estimation of the propensity score does not account for unobserved confounders such as household wealth, entrepreneurial skills and motivation that can also have effects on both the participation and outcome variables.

Conclusion

This paper examines the effects of mobile phones on households' uptake of credit in Cambodia, with data from the CSES conducted in 2014. The analysis is conducted with a PSM approach to evaluate the effects and address potential endogeneity issues of the use of mobile phones. The results suggest that mobile phones is very likely to induce households to take up credit offered by microfinance institutions, in particular to invest in non-agricultural investment activities, but to discourage households from using credit for non-productive activities. These results reveal that the use of mobile phones promotes financial inclusion in terms of households' access to credit and borrowed amount. This study contributes to earlier studies (see, for example, Mihasonirina & Kangni, 2011; Mihasonirina & Kangni, 2012; Shashank, 2014; Maria & Frida, 2014) by quantifying the effects at the household level and in particular by showing that mobile phones promote the uptake of credit for investment in productive activities and reduce the use for non-productive activities.

The favourable effects of mobile phones on financial inclusion is very likely to be attributed to their transaction-costs-reducing effects. Users of mobile phones can have easier access to a large amount of information, in particular on the process of applying for credit and on financial knowledge through by-phone communication and social networks, thus very likely managing business financed by credit more efficiently and then reducing business risk. Therefore, with such information, the users are very likely to be induced to take out credit to undertake investments in income-generating activities, especially non-agricultural investment as evidenced by the study results.

[6] Becker and Caliendo (2007) proposed "mhbounds" Stata command to conduct the Rosenbaum bounds test. Nevertheless, the Mantel-Haenszel statistics produced by the mhbounds can be only applied to binary outcome variables. However the borrowed amount in the current study is continuous, the current study also employs rbounds Stata command to conduct the sensitivity test for this outcome variable, following Clémont (2011) and Aakvik (2001).

Finally, the current study is limited by unobserved confounders that cannot be accounted for by the PSM approach. Furthermore, it has its limitations in the data because the panel data is unavailable and the data used in the analysis is not ideal for estimating treatment effects. Moreover, the data cannot allow the analysis to distinguish between smartphones and non-smartphones. Smartphones may have more effects on the access to financial services than do non-smartphones because they can be used with internet. Furthermore, the financial inclusion in this study is measured in terms of households' uptake of credit; however, it is only one of the financial services offered by financial institutions. Other financial services including deposit bank accounts, money transfer, emoney and so forth should be also included in the analysis of financial-inclusion-promoting effects of mobile phones. With such accurate data, one can improve this study with more appropriate technical approach to quantifying the financial-inclusion-promoting effects of mobile phones with more plausible results. This is an opportunity for future studies when better data is available.

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Appendix

Appendix A1

The Summary of the Implementation of PSM

In general, there are five steps in implementing the PSM. In step 1, the propensity score is estimated. Step 2 selects matching algorithm. Step 3 checks the overlap or common support condition. Step 4 evaluates the quality of matching or checks the balancing property. However, steps 3 and 4 can be done together (see, for example, Asfaw et al., 2012). Step 5 checks the sensitivity of the estimation of effects to unobserved confounders.

(a) Propensity Score Estimation

The propensity score is the probability of using mobile phones $\Pr(M_i = 1|Z_i)$ which will be estimated using either the probit or logit model, the choice of which model is the best is less discussed in the literature when the treatment is binary (Caliendo & Kopeining, 2008). Following the majority of previous studies, the current study uses the logit model to estimate the propensity score. The logit model describing the probability of using mobile phones is specified following Equation (1).

(b) Matching Approaches

Several matching methods have been developed in the literature, which can be used to match the users with the non-users that have very similar propensity scores to the scores of the users. These matching methods include nearest neighbor, stratification and interval, caliper and radius and kernel matching among others. All matching approaches should asymptotically produce the same outcomes. Nevertheless, in practice, one tends to face trade-offs in terms of bias and efficiency once preferring one method to the other (Caliendo & Kopeinig, 2008). However, in the literature, there is not a clear guidance about which method is the best and the adoption is very likely to depend on the question to be investigated.

Following Asfaw et al. (2012), the current study adopts the nearest-neighbor matching (NNM) and Kernel matching (KM) methods.[7] The NNM matches outcomes of each user with outcomes of non-users with a propensity score that is closest to the score of the users, and is carried out with replacement $(n \geq 1)$. Thus, this approach allows the matching of a given comparison unit (matched control) with more than one treated unit. Similar to Clément (2011), the current study uses a generalized NNM, the nearest five-neighbor matching approach, which takes the average outcomes of the nearest five comparison units as the counterfactual for individual treated units. Alternatively, the study also estimates the ATT using the KM with Gaussian type (normal) and bandwidth parameter fixed at 0.06 (following Clément (2011)), in part, to check the robustness. The KM estimates the ATT by matching each treated unit with a weighted sum of comparison units, assigning the greatest weight to comparison units with the nearest propensity score (Heckman et al., 1998).

(c) Common Support Restriction and Balancing Property

[7] The current study uses the psmatch2 Stata command proposed by Sianesi (2004) to estimate the matching results.

Given that the matching conditions on the propensity score in lieu of covariates, it is necessary to check whether the matching approach can balance the distribution of the covariates in the treated and control groups. In doing so, one needs to compare the estimated results before and after matching and, then, check whether any differences in the covariates of the two groups in the matched sample still exist after conditioning on the score (Caliendo & Kopeinig, 2008). Normally, the balancing test is conducted after matching to verify that the differences in covariates have been discarded, in which the comparison group that has been matched can be a credible counterfactual. There are several techniques of balancing test in the literature; however, the mean absolute standardized bias between the users and the non-users proposed by Rosenbaum and Rubin (1983) is commonly used.

Furthermore, Sianesi (2004) suggested comparing the pseudo-R^2 and p-values of the likelihood ratio test of the joint nonsignificance of all the covariates from the estimated logit model before and after matching samples. The structural differences in covariates distribution between the two sample groups should not exist after matching. Thus, the pseudo-R^2 should decrease and the joint nonsignificance of the covariates should be accepted (or the p-values should not be significant after matching).

(d) Sensitivity

Although the PSM approach compares the differences between the outcome variables of users and non-users with similar characteristics, it is unable to correct unobservable bias due to only accounting for observed factors. That is, it is almost impossible to test the unconfoundedness assumption conditional either on covariates or propensity score. This assumption could not be easily satisfied if unobserved confounders simultaneously affect the potential outcomes and the decision regarding the use of mobile phones. Thus, it is also important to perform a robustness check or sensitivity check of the estimated results subject to hidden bias. The robustness check of estimated results has been an increasingly important assignment in the empirical literature on effect evaluation (Becker & Caliendo, 2007). The estimated results might not only sensitive to unobserved factors but also to different specifications although some studies argue that the results of matching are independent of the specifications (Zhao, 2005).

There are several approaches used in the literature to check the sensitivity of the estimated results. For example, the "nnmatch" procedure proposed by Abadies et al. (2004) and the bounds method introduced by Rosenbaum (2002) can be adopted to check the sensitivity. However, the Rosenbaum approach is easier to be implemented and commonly used in most of empirical literature on effects evaluation. Recent implementations of the Rosenbaum approach can be found in DiPrete and Gangl (2004), Caliendo and Kopeinig (2008) or Clément (2011). The approach is briefly outlined as follows.

Now, let's assume that unobservable factors ε_i simultaneously influence the potential outcomes and treatment. Therefore, with the presence of ε_i, the CIA can be written as follows:

$$\left(Y_{1i}^T, Y_{0i}^C\right) \perp M_i | P(Z_i), \varepsilon_i \tag{12}$$

The probability of being in the treatment (participating in markets) is given by:

$$P\left(M_i = 1 \middle| P(Z_i, \varepsilon_i)\right) = F(\alpha Z_i + \psi \varepsilon_i) \tag{13}$$

where Z_i is a set of observed covariates, ε_i is a set of unobserved confounders, and $F(.)$ is the logistic distribution function. ψ is zero if the estimated results are not subject to hidden bias; that is, the treatment assignment is only conditional on or determined by the observed covariates. Let's further define $P(Z_i)/(1-P(Z_i))$ and $P(Z_j)/(1-P(Z_j))$ as the odd of being in the treatment group and control group, respectively. Then, the odd ratio can be derived as follows:

$$\frac{P(Z_i)/(1-P(Z_i))}{P(Z_j)/(1-P(Z_j))}=\frac{P(Z_i)(1-P(Z_j))}{P(Z_j)(1-P(Z_i))}=\frac{exp(F(\alpha Z_i+\psi\varepsilon_i))}{exp(F(\alpha Z_j+\psi\varepsilon_j))} \tag{14}$$

Under the CIA condition, Z_i and Z_j should be the same to ensure that units with similar characteristics take equal chance of receiving the treatment (more extensive discussion can be found in Rosenbaum (2002)). Thus, Equation (14) can be rewritten as follows:

$$\frac{P(Z_i)(1-P(Z_j))}{P(Z_j)(1-P(Z_i))} = exp[\psi(\varepsilon_i - \varepsilon_j)] \tag{15}$$

Equation (15) shows that the CIA is not satisfied if $\psi \neq 0$ and $\varepsilon_i \neq \varepsilon_j$. But, the estimates are free of hidden bias if the odd ratio is equal to 1. From Equation (15), ψ and $\varepsilon_i - \varepsilon_j$ can be computed to determine how strong the unobserved confounders undermine the matching estimates. Therefore, by assuming that $\Gamma = e^{\psi}$, the Rosenbaum bounds can be given by:

$$\frac{1}{\Gamma} \leq \frac{P(Z_i)(1-P(Z_j))}{P(Z_j)(1-P(Z_i))} \leq \Gamma \tag{16}$$

If $\Gamma = 1$ or $\psi = 0$, it means that hidden bias does not happen. If the values of Γ increase, it implies that there is the increasing effects of unobserved confounders in the treatment selection. For the different values of Γ, the Rosenbaum bounds approach employs matching estimates to compute confidence intervals of the treatment effects. If the lowest Γ yielding an interval of confidence that encompasses zero is relatively small, the estimated treatment effects are very likely to be subject to such an unobserved confounder (Duvendack & Palmer-Jones, 2012). According to the literature on the application of PSM approach, if the lowest Γ, which is less than 2, produces a confidence interval encompassing zero, the estimates are sensitive to unobserved confounders (see, for example, Caliendo & Kopeinig, 2008; Clémont, 2011; Duvendack & Palmer-Jones, 2012).

Table A1. Differences in standardized means for individual covariates for the KM method

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p> |t|	V(T)/ V(C)
HH's age	U	3.7682	3.7102	19.4		5.40	0.000	0.77*
	M	3.768	3.7781	-3.4	82.6	-0.91	0.364	1.02
HH's age squared	U	14.277	13.867	18.5		5.14	0.000	0.77*
	M	14.275	14.35	-3.4	81.7	-0.90	0.366	1
HH gender	U	.14468	.20713	-16.5		-4.57	0.000	0.75*
	M	.1448	.14566	-0.2	98.6	-0.06	0.952	1

H members < 15	U	1.6867	1.8254	-10.6		-2.98	0.003	0.88*
	M	1.688	1.6926	-0.3	96.7	-0.09	0.929	0.94
H members > 64	U	.16307	.1804	-3.9		-1.11	0.267	0.92
	M	.1632	.17557	-2.8	28.6	-0.71	0.479	0.95
Working-age members	U	3.4972	2.8717	42.6		12.40	0.000	1.45*
	M	3.492	3.5223	-2.1	95.2	-0.48	0.634	0.99
Landholding	U	.00093	-.18213	15.9		4.62	0.000	1.38*
	M	-0.00106	-0.00423	0.3	98.3	0.07	0.945	1.32*
HH's primary education	U	.48201	.49131	-1.9		-0.53	0.598	1
	M	.4824	.49207	-1.9	-4	-0.48	0.629	1
HH's secondary education	U	.34692	.18218	38		11.10	0.000	1.52*
	M	.3464	.3459	0.1	99.7	0.03	0.979	1
HH's higher education	U	.00799	.01114	-3.2		-0.89	0.371	0.72*
	M	.008	.00677	1.3	60.9	0.36	0.720	1.18*
Farmer	U	.73541	.88508	-38.9		-11.54	0.000	1.91*
	M	.736	.74473	-2.3	94.2	-0.50	0.619	1.02
Professional	U	.06075	.0098	27.9		8.84	0.000	5.88*
	M	.06	.05199	4.4	84.3	0.87	0.384	1.14*
Non-agricultural worker	U	.07434	.01425	29.5		9.28	0.000	4.90*
	M	.0744	.07178	1.3	95.6	0.25	0.802	1.03
Agricultural worker	U	.00799	.0245	-13.1		-3.47	0.001	0.33*
	M	.008	.00773	0.2	98.3	0.08	0.939	1.04
Other career	U	.00959	.00624	3.8		1.11	0.268	1.53*
	M	.0096	.01089	-1.5	61.7	-0.32	0.750	0.88*
Ethnicity	U	.96962	.9706	-0.6		-0.16	0.871	1.03
	M	.9696	.97336	-2.2	-284.8	-0.56	0.572	1.14*

* if variance ratio outside [0.90; 1.12] for U and [0.89; 1.12] for M

Table A2. Differences in standardized means for individual covariates for the NNM method

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	p> |t|	V(T)/ V(C)
HH's age	U	3.7682	3.7102	19.4		5.40	0.000	0.77*
	M	3.8377	3.8727	-11.7	39.6	-1.64	0.101	1
HH's age squared	U	14.277	13.867	18.5		5.14	0.000	0.77*
	M	14.785	15.055	-12.2	34.1	-1.68	0.093	0.96
HH gender	U	.14468	.20713	-16.5		-4.57	0.000	0.75*
	M	.09804	.07203	6.9	58.3	1.05	0.293	1.32*
H members < 15	U	1.6867	1.8254	-10.6		-2.98	0.003	0.88*
	M	1.3961	1.3984	-0.2	98.4	-0.02	0.982	0.98
H members > 64	U	.16307	.1804	-3.9		-1.11	0.267	0.92
	M	.13333	.18255	-11.2	-184	-1.33	0.184	0.61*
Working-age members	U	3.4972	2.8717	42.6		12.40	0.000	1.45*
	M	4.3137	4.4388	-8.5	80	-0.83	0.407	0.95
Landholding	U	.00093	-.18213	15.9		4.62	0.000	1.38*
	M	.25574	.00617	21.7	-36.3	2.21	0.028	1.11
HH's primary education	U	.48201	.49131	-1.9		-0.53	0.598	1
	M	.41176	.45778	-9.2	-394.8	-1.05	0.296	0.98
HH's secondary education	U	.34692	.18218	38		11.10	0.000	1.52*
	M	.50196	.47902	5.3	86.1	0.52	0.605	1
HH's higher education	U	.00799	.01114	-3.2		-0.89	0.371	0.72*
	M	.00784	.00588	2	37.6	0.27	0.789	1.33*
Farmer	U	.73541	.88508	-38.9		-11.54	0.000	1.91*
	M	.63137	.59065	10.6	72.8	0.94	0.347	0.96
Professional	U	.06075	.0098	27.9		8.84	0.000	5.88*
	M	.07059	.04837	12.2	56.4	1.06	0.290	1.43*
Non-agricultural worker	U	.07434	.01425	29.5		9.28	0.000	4.90*
	M	.07451	.05902	7.6	74.2	0.70	0.484	1.24
Agricultural worker	U	.00799	.0245	-13.1		-3.47	0.001	0.33*

	M	0	0	0	100	.	.	.*
Other career	U	.00959	.00624	3.8		1.11	0.268	1.53*
	M	.01569	.0315	-17.8	-371.3	-1.18	0.240	0.51*
Ethnicity	U	.96962	.9706	-0.6		-0.16	0.871	1.03
	M	.96863	.98314	-8.5	-1385.1	-1.07	0.286	1.83*

* if variance ratio outside [0.90; 1.12] for U and [0.78; 1.28] for M

Table A3. Sensitivity check

	Gamma	Significance level		Hodges-Lehmann point estimates		95% confidence Intervals	
		sig+	sig-	t-hat+	t-hat-	CI+	CI-
Formal borrowing	1	0.000	0.000	0.046	0.046	0.039	0.052
	1.5	0.000	0.000	0.026	0.069	0.018	0.079
	2	0.066	0.000	0.008	0.098	-0.003	0.157
	2.5	0.951	0.000	-0.013	0.348	-0.049	0.468
	3	1.000	0.000	-0.062	0.480	-0.144	0.503
Formal productive borrowing	1	0.985	0.985	-0.117	-0.117	-0.155	-0.066
	1.5	1.000	0.000	-0.188	0.256	-0.195	0.265
	2	1.000	0.000	-0.201	0.273	-0.207	0.279
	2.5	1.000	0.000	-0.210	0.282	-0.214	0.289
	3	1.000	0.000	-0.215	0.290	-0.220	0.296
Agricultural borrowing	1	0.000	0.000	0.126	0.126	0.115	0.133
	1.5	0.961	0.000	-0.203	0.148	-0.247	0.155
	2	1.000	0.000	-0.280	0.163	-0.301	0.171
	2.5	1.000	0.000	-0.309	0.175	-0.321	0.185
	3	1.000	0.000	-0.324	0.188	-0.331	0.201
Non-agricultural borrowing	1	0.000	0.000	-0.324	-0.324	-0.329	-0.318
	1.5	0.000	0.000	-0.339	-0.300	-0.344	-0.289
	2	0.000	0.000	-0.348	-0.271	-0.352	-0.250
	2.5	0.000	0.000	-0.354	-0.236	-0.358	-0.203
	3	0.000	0.022	-0.359	-0.194	-0.362	-0.064
Borrowing for consumption	1	0.686	0.686	0.011	0.011	-0.160	0.046
	1.5	0.000	1.000	-0.327	0.095	-0.339	0.106
	2	0.000	1.000	-0.349	0.116	-0.358	0.124
	2.5	0.000	1.000	-0.364	0.129	-0.373	0.139
	3	0.000	1.000	-0.374	0.142	-0.381	0.151
Other non-productive credit use	1	0.000	0.000	-0.203	-0.203	-0.214	-0.187
	1.5	0.000	0.796	-0.227	0.114	-0.232	0.213
	2	0.000	1.000	-0.238	0.233	-0.243	0.241
	2.5	0.000	1.000	-0.246	0.245	-0.251	0.251

	3	0.000	1.000	-0.252	0.253	-0.256	0.260
Formal borrowed amount	1	0.000	0.000	365708	365708	214675	542548
	1.5	0.846	0.000	-62181	926039	-172730	1100000
	2	1.000	0.000	-288200	1400000	-382520	1700000
	2.5	1.000	0.000	-435407	1900000	-522142	2200000
	3	1.000	0.000	-542517	2300000	-620824	2700000

* gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= 0.95)
CI- - lower bound confidence interval (a= 0.95)