

Microfinance Banks and Financial Inclusion*

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Abstract

We examine how the geographical proximity to a microfinance bank affects financial inclusion. We study the expansion of the branch network of ProCredit banks in South-East Europe between 2006 and 2010. We report three main findings: First, ProCredit is more likely to open a new branch in areas with a large share of low-income households. Second, in locations where ProCredit opens a new branch the share of banked households increases more than in locations where it does not open a new branch. Third, this increase is particularly strong among low-income households, older households, and households which rely on transfer income.

JEL classification: G21, L2, O16, P34

1. Introduction

Financial services for the poor are increasingly provided by commercially orientated, deposit taking microfinance banks (MFBs). Among the 485 largest microfinance institutions worldwide, 377 (78%) are regulated deposit taking institutions, among which 240 are

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profit seeking.¹ In 2011, these large regulated commercial microfinance institutions boasted a combined asset volume of 85 billion USD. The role of commercial MFBs is especially important in emerging economies. In Eastern Europe and Central Asia, for example, 98 of the 101 largest microfinance providers are regulated and 67 of these institutions are profit-seeking MFBs. In this region alone, commercial MFBs together hold a total asset volume of over 14 billion USD.

International donors and development banks support commercial MFBs through subsidized credit lines and equity participation. This support is rationalized by the conjecture that MFBs offer financial services to households which are not served by “ordinary” retail banks (RBs). In emerging economies, however, RBs with large branch networks often provide a broad coverage of financial services across the country. For example in Albania, a country with a population of 2.8 million, the largest RB boasted 102 branches in 2010. The widespread access to ordinary RBs gives rise to the question whether public funding of MFBs is warranted in emerging economies.

In this paper we examine to what extent MFBs foster financial inclusion in emerging economies. We study how the geographical proximity to a new MFB branch affects the use of bank accounts by low-income households in South-East Europe. Our analysis is based on four countries in which the major MFB in the region—ProCredit Bank—expanded its branch network substantially in recent years: Albania, Bulgaria, Macedonia, and Serbia. Our main data source is the EBRD Life in Transition Survey (LITS). This survey provides information on the use of bank accounts, socioeconomic characteristics and geographical location of over 8,000 households in our four countries in 2006 and 2010. We geocode the location of households in the survey and match this data to information on the branch network of ProCredit Bank in 2006 and 2010, as well as the branch network of the major RBs in each country. As the main RBs have large branch networks in all four countries we study the additional effect that new ProCredit branches have in regions which are already served by at least one RB.

Our empirical analysis is guided by hypotheses derived from a model which examines households’ decisions to open bank accounts in a framework where heterogeneous banks choose the location of their branch networks. First, we examine whether ProCredit is more likely to open new branches in regions with a large economically active population as well as a large share of low-income households (location effect). Second, we assess the impact of new ProCredit branches on the share of banked households in the proximity (volume effect) in a difference-in-difference framework. We assign households in regions where ProCredit opens a new bank branch between 2006 and 2010 to a treated group and households in regions where ProCredit does not open a branch to the control group. Households that are surveyed in 2006 constitute the pre-treatment observations while households surveyed in 2010 constitute the post-treatment observations. Third, we conduct subsample analyses in order to study whether the estimated difference-in-difference effect is larger for low-income households compared with high-income households (composition effect).

Our results suggest that ProCredit promotes financial inclusion in South-East Europe. First, we find that ProCredit is more likely to open new branches in regions with strong

1 Source: www.mixmarket.org. The figures are based on 2011 data for large microfinance institutions (as classified by MIX Market) in Latin America and the Caribbean, Sub-Saharan Africa, North Africa and the Middle East, Eastern Europe and Central Asia, South Asia as well as East Asia and the Pacific.

economic activity, a high population density, and a larger presence of RB branches, and also in regions which have a large share of low-income households. Second, we show that in those locations where ProCredit opens a new branch the share of households with a bank account increases significantly more between 2006 and 2010 than in locations where ProCredit does not open a new branch. The economic magnitude of this effect is significant: Our multivariate estimates indicate that ProCredit leads to a 16–21 percentage point increase in the use of bank accounts. A placebo test in which we replace ProCredit in each country by a RB that showed a similar branch expansion between 2006 and 2010 indicates that our findings are specific to ProCredit. Third, our subsample analyses point to a particularly strong effect of new ProCredit branches on the use of bank accounts among low-income households, older households, and households that rely on transfer income.

South-East Europe provides an ideal laboratory to study the impact of commercial MFBs on financial inclusion in an emerging economy context. First, despite substantial economic growth over the last decade the use of financial services is still low in the region. In the four countries covered by our analysis the incidence of bank accounts varied between 18% and 55% of households in 2006.² Second, between 2006 and 2010 the number of bank branches and the share of households with bank accounts increased substantially in all four countries. Third, in this region we can examine the additional effect of a MFB (ProCredit) on financial inclusion, controlling for the presence of ordinary RBs.

From a policy perspective, emerging Europe provides a highly relevant setting to study the potential benefits of public financial support to commercial MFBs. This region has seen considerable foreign direct investment in the retail banking sector over the past decade (see e.g. Giannetti and Ongena, 2009; Haselmann, Pistor, and Vig, 2010; Ongena, Popov, and Udell, 2013; Claeys and Hainz, 2014). Today, international banking groups (e.g. Raiffeisen International, UniCredit) maintain retail networks throughout the region. This raises the question whether public investment in the banking sector, e.g. by supporting MFBs, is necessary in these markets. If the retail networks of international banking groups provide similar banking services as MFBs, then public support of the latter is hardly warranted.

Our paper is related to the empirical literature which explores how the structure of the banking sector affects financial inclusion in developing and emerging economies.³ Allen et al. (2014) examine the relationship between household proximity to a MFB and household use of financial services in sub-Saharan Africa.⁴ Similar to our analysis, they study the expansion of the branch network of a large Kenyan MFB (Equity Bank) between 2006 and 2009. They document that compared with other banks, the MFB is more likely to open branches in districts with low population density. Moreover, they show that new MFB branches in a district are associated with a stronger increase in the use of financial services than new branches of other banks. This effect is, as in our data, especially strong among the low-income population. Our analysis complements that of Allen et al. (2014) in two important ways: First, we confirm the impact of commercial MFBs on financial inclusion in

2 By comparison similar survey data show that in Western Europe more than 95% of all households hold bank accounts (Beck and Brown, 2011).

3 See Karlan and Murdoch (2010) for a comprehensive overview of the empirical literature on access to finance. For recent evidence on the impact of access to saving services see, e.g., Ashraf, Karlan, and Yin (2010), Brune et al. (2011), and Dupas and Robinson (2013).

4 For further recent evidence on access to finance in sub-Saharan Africa see Beck et al. (2010), Aterido, Beck, and Iacovone (2013), and Honohan and King (2013).

an emerging market context where foreign-owned RBs maintain large branch networks. Second, we show at a more granular level, that even in locations where RBs already have a branch, a new MFB branch can enhance financial inclusion—at least in the initial years after its opening. Our more granular analysis is based on matching the precise geographic coordinates of households and bank branches. This use of geographic coordinates also allows us to control for local economic activity by matching household and bank locations with satellite information on nightlight intensity.

Our findings contribute to the broader discussion on bank-ownership structure and access to finance. Beck, Demirgüç-Kunt, and Martinez Peria (2007) use cross-country aggregate data on branch penetration and number of bank accounts to document that government and foreign ownership of banks is negatively associated with access to finance. Beck, Demirgüç-Kunt, and Martinez Peria (2008) examine cross-country information on product terms of large banks and find that barriers for bank customers are higher where banking systems are predominantly government-owned and lower where there is more foreign bank participation. Allen *et al.* (2012) study household-level data for 123 countries and provide evidence that the use of financial services, especially among low-income households, is strongly related to the costs of banking services and the geographical proximity to financial service providers. They find that the perceived availability of financial services is positively related to state ownership and negatively related to foreign ownership in the banking sector. Beck and Brown (2013) provide evidence that in emerging Europe financially opaque households (households without formal income sources and pledgeable assets) are at a relative disadvantage in credit markets dominated by foreign banks. We contribute to this literature by documenting how the business models of banks, *i.e.*, a focus on serving low-income households by MFBs, affects financial inclusion in emerging markets.

We also contribute to the ongoing debate on the mission drift of commercial microfinance institutions. Examining income-statement and loan portfolio data for 124 of the largest microfinance institutions worldwide for the period 1999–2002, Cull, Demirgüç-Kunt, and Morduch (2007) find some evidence for a mission drift: Larger and more profitable microfinance institutions have higher average loan sizes and serve a lower share of female clients. Mersland and Strøm (2010) examine data for 379 microfinance institutions from seventy-four countries over the period 2001–08 and also find some evidence for a mission drift: More profitable institutions display higher average loan sizes. Their findings suggest, however, that mission drift may be contained if commercial microfinance providers become more cost-efficient. We contribute to this literature by providing household-level evidence (as opposed to bank-level evidence) on how commercial MFBs affect the use of bank accounts (as opposed to loan take up). Moreover, rather than comparing the outreach of commercial MFBs to that of non-profit microfinance institutions, we compare their outreach with that of RBs. In our view, this is the more relevant comparison for policy makers deciding on whether to support commercial MFBs, especially in emerging economies.

The remainder of this paper is organized as follows. In Section 2, we present a model of household deposit and bank location decisions and derive hypotheses for our empirical analysis. Section 3 describes the institutional setting and Section 4 our data. Sections 5 and 6 present our methodology and main results. Section 7 presents robustness checks and Section 8 concludes.

2. Model and Hypotheses

In this section, we derive our empirical hypotheses from a model which explores the choice of heterogeneous households to open bank accounts. Our model is related to that of Mulligan and Sala-i-Martin (2000) who study the extensive margin of holding bank deposits as opposed to cash money. We extend their framework to model the choice of heterogeneous banks to open branches, depending on the expected number of clients and competition in a region.

2.1 Model Set Up

Households live in one of L regions in the economy. There are n_l households in each region l . Each household i has wealth $A_i \in [\underline{A}, \bar{A}]$ and has to decide whether to hold its wealth in cash or to deposit it in a bank.

Households face a fixed cost $\varphi_j > 0$ of opening a bank account with bank j . The return to a household from opening an account is increasing in wealth. For simplicity we assume that the return is linear in wealth with R_j being the return per unit of wealth from an account with bank j . Households only consider local branches of banks when choosing to open a bank account. That is, we assume that the costs of opening an account at a branch in other regions are prohibitively high even for households with the highest wealth level $\bar{A}$.⁵

There are two banks in the economy: a MFB and a RB. Both banks choose which regions l to locate branches in. We assume for simplicity that each bank type j has fixed costs of running a branch β_j and earns a fixed (exogenous) profit per client served π_j .

We assume that the decisions of banks and households take place in two steps: First, the MFB and the RB decide simultaneously in which regions they open branches. Second, given the available bank branches in their region, households decide whether to open a bank account, and—if both banks are present—at which bank to do so. In the following we solve the model by backward induction.

2.2 The Household Deposit Decision

Consider a region l in which at least one bank has opened a branch. When deciding on whether to open an account at bank j households compare the benefits of the account to the fixed cost of opening it: $R_j \cdot A_i \geq \varphi_j$. Condition (1) denotes the minimum level of assets required for a household i to yield a positive return from opening an account at bank j :

$$A_i \geq \frac{\varphi_j}{R_j}. \quad (1)$$

We assume that the costs of opening a bank account are lower at the MFB than at the RB: $\varphi_{\text{MFB}} < \varphi_{\text{RB}}$. Lower costs may be related to lower fees, lower minimum balances for deposit accounts, less complicated procedures or lower “cultural barriers” between bank staff and households. We further assume that the return per unit wealth is higher at the RB than at the MFB: $R_{\text{RB}} > R_{\text{MFB}}$. The higher return at the RB can be related to access to a broader range of financial services (e.g., electronic payment services, wealth management).

5 This is in line with the evidence of Allen et al. (2012) suggesting that geographical distance to financial service providers is a main barrier to households' use of these services.

The key assumption in our model is that the minimum wealth level required to benefit from a MFB account is lower than that required at a RB. This is the case if:

$$\frac{\varphi_{\text{MFB}}}{R_{\text{MFB}}} < \frac{\varphi_{\text{RB}}}{R_{\text{RB}}} . \quad (2)$$

Based on Conditions (1) and (2), we distinguish four types of households with different demand for bank accounts depending on their wealth level $A_i \in [\underline{A}, \bar{A}]$:

- Households with very low wealth levels $\bar{A} \leq A_i < \frac{\varphi_{\text{MFB}}}{R_{\text{MFB}}}$ will not open a bank account, no matter which type of bank has a branch in their region (Type 1 households).
- Households with low wealth levels $\frac{\varphi_{\text{MFB}}}{R_{\text{MFB}}} \leq A_i < \frac{\varphi_{\text{RB}}}{R_{\text{RB}}}$ will only open an account if there is a branch of the MFB in their region (Type 2 households).
- Households with moderate wealth levels $\frac{\varphi_{\text{RB}}}{R_{\text{RB}}} \leq A_i < \frac{\varphi_{\text{RB}} - \varphi_{\text{MFB}}}{R_{\text{RB}} - R_{\text{MFB}}}$ will open an account if either of the banks has a branch in their region, but prefer an account at the MFB (Type 3 households).
- Households with high wealth levels $\frac{\varphi_{\text{RB}} - \varphi_{\text{MFB}}}{R_{\text{RB}} - R_{\text{MFB}}} \leq A_i \leq \bar{A}$ will open an account if either of the banks has a branch in their region, but prefer the RB (Type 4 households).

2.3 The Bank Branch Location Decision

The decision to open a branch in a region is determined by the number of expected clients and the fixed costs of opening a branch. As each bank type j has fixed costs of running a branch β_j and earns a fixed income per client π_j the number of clients required for a branch of bank j in region l to break even must exceed $\frac{\beta_j}{\pi_j}$.

We assume that banks know the total population in each region n_l as well as the share of Type 1–Type 4 households in each region $\delta_{l,1}, \delta_{l,2}, \delta_{l,3}, \delta_{l,4}$. This implies that banks are fully informed about the wealth distribution in each region l . Banks also know the costs and returns of opening a bank account for households at each bank type. Moreover, we assume that banks are informed about the costs of opening a branch and income per client for both bank types.

Given that Type 3 and Type 4 households will open an account at either bank, the decision of the MFB to locate in a region depends on the location decision of the RB (and vice-versa). The number of clients served by the MFB branch is equal to:

$$\begin{aligned} & (\delta_{l,2} + \delta_{l,3}) \cdot n_l && \text{if the RB is in the region} \\ & (\delta_{l,2} + \delta_{l,3} + \delta_{l,4}) \cdot n_l && \text{if the RB is not in the region} \end{aligned} \quad (3)$$

The number of clients served by the RB is equal to:

$$\begin{aligned} & (\delta_{l,4}) \cdot n_l && \text{if the MFB is in the region} \\ & (\delta_{l,3} + \delta_{l,4}) \cdot n_l && \text{if the MFB is not in the region} \end{aligned} \quad (4)$$

Based on Equations (3) and (4) we can calculate the profits of both banks from having a branch in region l :

- If both banks are in a region the MFB earns $\pi_{\text{MFB}} \cdot (\delta_{l,2} + \delta_{l,3}) \cdot n_l - \beta_{\text{MFB}}$ while the RB earns $\pi_{\text{RB}} \cdot \delta_{l,4} \cdot n_l - \beta_{\text{RB}}$.
- If the MFB is in a region but the RB is not then the MFB earns $\pi_{\text{MFB}} \cdot (\delta_{l,2} + \delta_{l,3} + \delta_{l,4}) \cdot n_l - \beta_{\text{MFB}}$ while the RB earns 0.
- If the MFB is not in a region but the RB is then the MFB earns 0 while the RB earns $\pi_{\text{RB}} \cdot (\delta_{l,3} + \delta_{l,4}) \cdot n_l - \beta_{\text{RB}}$.

2.4 Model Results and Empirical Hypotheses

Given the income and cost structure of each bank type $\pi_{\text{MFB}}, \beta_{\text{MFB}}, \pi_{\text{RB}}, \beta_{\text{RB}}$ and the population size of a region n_i we derive the following results from our model:

Branch location of the MFB: The MFB is more likely to have a branch in regions with a large economically active population n_i among which a large share has a low or moderate wealth level $\delta_{i,2}, \delta_{i,3}$. If the RB is not located in a region the share of high-wealth households $\delta_{i,4}$ also positively affects the decision of the MFB to open a branch.

Financial inclusion: If a MFB has a branch in a region the share of households with a bank account is higher than if the same region is served just by the RB. The additional account holders are characterized by low levels of wealth (Type 2 households).

Note that we have assumed that the relative costs of opening and maintaining a bank account at a MFB compared with a RB ($\varphi_{\text{MFB}} < \varphi_{\text{RB}}$) are identical for all households. This is likely to be the case for the explicit costs of account opening and maintenance, but less so for the non-financial costs induced by different procedures and “cultural barriers” between bank staff and households. Households may differ substantially in their familiarity with banks and their procedures, e.g. due to age, education, economic activity, or social background. Those households with high non-financial costs of using RBs will be more likely to open an account with a MFB. As a consequence we would expect that—conditional on the income distribution—MFBs locate in areas populated by households with high barriers to using RBs. Moreover, in areas where MFBs locate, these banks not only serve lower-income households, but also households which are less familiar with banks and their procedures.

As we discuss in Section 4, our empirical analysis studies the expansion of the branch network of ProCredit Bank in South-East Europe between 2006 and 2010. We hereby focus our analysis on regions which are already served by at least one RB in 2006 and thus examine the additional effect of a new MFB branch in fostering financial inclusion among households in the initial years after its opening. We study three specific research questions: (i) In which regions does ProCredit open a branch? (ii) Does the share of banked households increase in regions where ProCredit opens a new branch compared with regions where ProCredit does not open a branch? (iii) Which types of households display the largest increase in the incidence of bank accounts in regions where ProCredit locates when compared with regions where it does not locate?

Based on the results of our theoretical model we establish the following two hypotheses:

Hypothesis 1 (location effect): Given the presence of a RB branch in a region, ProCredit bank is more likely to open a new branch in regions with a large economically active population among which there is a substantial share of households with low income.

Hypothesis 2 (volume and composition effect): Given the presence of a RB, the share of households with a bank account increases more in regions where ProCredit opens a new branch compared with regions where it does not open a branch. The increase in the share of the banked population is stronger among low-income households than among high-income households. Moreover, the increase in the share of the banked population is stronger among households that face higher non-financial barriers to using RBs.

3. Institutional Background

Our analysis studies the expansion of the branch network of the ProCredit banks in four countries of South-East Europe, Albania, Bulgaria, Macedonia, and Serbia, between 2006

and 2010. ProCredit group consists of twenty-one commercial MFBs in emerging and developing countries in Eastern Europe, Latin America, and Africa.⁶ All ProCredit banks operate under a local banking license and are regulated by the local banking supervisory agency. ProCredit Holding that holds a controlling stake in all ProCredit banks is owned by a mix of private and public shareholders.⁷ The public shareholders expect the ProCredit banks to operate profitably but are not driven by profit maximization aims. They rather include the social return that ProCredit offers in their profit expectations as well. Besides, ProCredit banks may receive public support through subsidized credit lines from their public shareholders and other international donors. ProCredit views its business model as one of “socially responsible banking that seeks to be transparent, efficient, and profitable on a sustainable basis”. It believes that a “functioning and inclusive financial system makes a contribution to a country’s development” and puts the focus of its efforts on achieving this broader aim.

ProCredit offers a wide range of banking services to small and medium enterprises as well as to low- and middle-income savers. Besides small business loans ProCredit considers deposit facilities to be the most important of its core products. ProCredit values the direct and active contact to its (potential) clients and describes its approach as being the neighborhood bank for ordinary people. This approach implies lowering the barriers for (potential) clients to start a formal bank relationship by offering simple and transparent products, also and especially to underserved target groups. This approach also includes providing a wide range of information for customers on the bank web pages. (Potential) depositors, for instance, are informed that they should know the bank they deposit their money with and are then explained the business and lending model of ProCredit.

In sum, the ProCredit banks differ from RBs in important aspects such as their development-oriented business model, their subsidized funding from public sources, and their active and educational client approach.⁸ However, some of the products, including their terms, that they offer might not differ significantly from those that the RBs offer. And (as exemplified by our model in Section 2) MFBs and RBs may also have partially overlapping target customer groups.

We focus our analysis on Albania, Bulgaria, Macedonia, and Serbia over the period 2006–10 for three reasons: First, during this period the ProCredit banks in all four countries expanded their branch networks considerably. As documented by Table AI in the Appendix the number of ProCredit branches increased from 16 to 42 in Albania, from 42 to 87 in Bulgaria, from 16 to 42 in Macedonia, and from 35 to 83 in Serbia. Second, in all

6 See <http://www.procredit-holding.com> for more information. The quotes on ProCredit’s business model are also taken from this web page.

7 As of December 2010, the shareholders are IPC GmbH, ipc-invest GmbH and Co KG, KfW, DOEN, IFC, BIO, FMO, TIAA-CREF, responsAbility, PROPARCO, FUNDASAL, and Omidyar-Tufts Microfinance Fund.

8 At the same time, ProCredit banks are similar to other commercial microfinance banks such as the banks of the Access Group (<http://www.accessholding.com/>), and also to those institutions of FINCA that have been or are about to be transformed into banks with licenses (<http://www.finca.org/who-we-are/business-model/>). ProCredit banks differ from other, non-profit, microfinance institutions in their ability to collect savings because they are formal, licensed banks that are regulated and supervised by the national authorities and in their aim to become financially self-sustainable in the long-term.

of these countries the use of bank accounts by households was low in 2006 (between 18% and 55%), but increased sharply between 2006 and 2010 (Beck and Brown, 2011). Third, for each of these countries we can match bank-branch location data to survey data which provide household-level information on the use of bank accounts in 2006 and 2010.⁹

In all four countries the ProCredit banks were founded in the early 2000s¹⁰ and had established a substantial branch network by 2006. However, ProCredit is neither the largest bank (measured by total assets) nor the most accessible bank (as measured by branch network) in any of the countries. Table AI in the Appendix shows that in 2006 the largest RB in Albania (Bulgaria, Macedonia, Serbia) had five (three, three, five) times more branches than ProCredit. Moreover, between 2006 and 2010 these RBs also expanded their branch networks substantially. Table AI in the Appendix also documents that the largest RBs in all four countries are either foreign-owned or state-owned. These conditions allow us to examine the impact of a commercially operated MFB on financial inclusion in a context which is common to many emerging economies: The economy is served by several RBs with large branch networks and many of these banks are controlled by foreign financial institutions or the domestic government.

4. Data

Our main data source is the EBRD-World Bank LITS which was conducted in 2006 and 2010 as a repeated cross-sectional survey. In each of the countries in our sample fifty to seventy-five Primary Sampling Units (PSUs) were randomly chosen for each survey wave.¹¹ Then twenty households within each PSU were randomly selected, resulting in 1,000–1,500 observations per country and survey wave.

The first part of the interviews was conducted with the person deemed to have the most knowledge on household issues (household head) and yields information on household composition, housing, expenses, and the use of (financial) services. For the second part of the survey, a randomly selected adult household member (respondent) was interviewed about attitudes and values as well as the personal work history, education, and entrepreneurial activity. For the purpose of our study, we use information from the first part of the survey to obtain indicators of household use of banking services, location, size, and income as well as the gender and age of the household head. From the second part of the survey, we obtain indicators of education, employment status, religion, and social integration. We drop all observations with missing household-level information which leads to a sample of 3,992 household-level observations in 2006 and 4,244 household-level observations in 2010.¹² Table AII in the Appendix provides the definitions of all variables which we employ in our analysis,

9 We do not include Bosnia, Romania, and Ukraine due to data limitations. We do not include Croatia in our study because the use of bank accounts was already very high in 2006.

10 Only in Albania a predecessor institution existed before it was renamed ProCredit and became a full-service commercial microfinance bank. In 2010, the majority owner of all four banks with between 80% and 90% of the shares was ProCredit Holding. The remaining shares were held by Commerzbank AG and the EBRD.

11 In each wave PSUs were randomly selected with the probability of selection proportional to PSU size.

12 See <http://www.ebrd.com/what-we-do/economic-research-and-data/data/lits.html> for details of the LITS survey questionnaire.

Table I. Use of bank accounts by country in 2006 and 2010

This table reports the share of households with a bank account on the PSU level per country in 2006 (Panel A) and in 2010 (Panel B). Definitions and sources of the variables are provided in [Table AII](#) in the Appendix.

Panel A: Primary sampling units (PSUs) in 2006		All countries	Albania	Bulgaria	Macedonia	Serbia
Share of households with account (per PSU)	Mean	0.28	0.19	0.18	0.20	0.55
	Minimum	0.00	0.00	0.00	0.00	0.00
	Maximum	0.90	0.70	0.70	0.90	0.90
Panel B: Primary sampling units (PSUs) in 2010		All countries	Albania	Bulgaria	Macedonia	Serbia
Share of households with account (per PSU)	Mean	0.53	0.45	0.29	0.58	0.69
	Minimum	0.00	0.00	0.00	0.00	0.00
	Maximum	1.00	1.00	0.94	1.00	1.00

while [Table AIII](#) in the Appendix provides summary statistics of these variables by survey wave.

4.1 Use of Bank Accounts

The main dependent variable in our empirical analyses is the dummy variable *Account* which indicates whether any member of the household has a bank account. [Table I](#) shows that the share of households which hold a bank account varies substantially across regions within each of the four countries. For example, in 2006 19% of the households in Albania have a bank account. However, in some PSUs 70% of the households have a bank account, while in other PSUs none of the surveyed households have an account. By 2010 the share of banked households in Albania increased to 45%. However, even in 2010 there are some regions in the country where none of the surveyed households have an account. [Table I](#) shows similar patterns for the share of households with bank accounts in Bulgaria, Macedonia, and Serbia. Thus, while the use of bank accounts increased substantially during our observation period, this development occurred very unevenly within each country.

4.2 Proximity to Bank Branches

The LITS data provides information on the village/municipality in which each PSU is located. For the four countries in our sample, we obtain the geographical coordinates of each PSU using Google maps. We obtain geographical information on the branch network of banks in each country in 2002, 2006, and 2010 from the EBRD. We augment this data with hand-collected information from banks’ websites and annual reports. Our branch location information covers five (in Macedonia three) major RBs that together account for more than 50% of the bank branches in each country.¹³ For each country we also gather

13 We have information on the number of all bank branches in each country in 2012 only and therefore base our ranking of banks in terms of the size of their branch networks on these numbers (see Supplementary Material). We resort to including five major retail banks from among the 10

information on the branch network of a RB that is similar to ProCredit in terms of its foreign ownership, size of its branch network in 2006, and the expansion of its branch network between 2006 and 2010 in order to run a placebo test as a robustness check for our results. We specify the exact location of each bank branch in terms of the latitude and longitude again using Google maps. [Table AI](#) in the Appendix lists all banks included in our analysis. Our Supplementary Material presents a cartographical overview of the locations of PSUs and bank branches by country in 2006 and 2010.

We measure the proximity between households and bank branches at each point in time with the dummy variables ProCredit close in 2006 (2010) and RBs close in 2006 (2010). These indicators are one if the nearest ProCredit branch or RB branch, respectively, is within a travel distance of 5 km of the center of the PSU in which a household is located in 2006 (2010). We use distance thresholds as opposed to continuous measures of travel distance in order to capture the idea that the fixed costs of opening and maintaining a bank account depend on whether a household is within walking, cycling, or local public transport distance of a bank branch or not. We employ a 5-km threshold as previous research suggests that even corporate clients typically bank with financial institutions that are within this narrow radius ([Petersen and Rajan, 2002](#); [Degryse and Ongena, 2005](#)). As a robustness test we employ a travel distance cut-off of 10 km (see [Section 7.2](#)).

[Table II](#) documents the proximity of the households in our sample to a ProCredit branch and RB branch in 2006 and 2010. Given that the LITS is a repeated cross-section survey with changing PSUs per wave we observe households either in 2006 or 2010. Importantly though, for each PSU we observe whether that PSU was close to a particular bank branch in 2006 as well as in 2010.

Panel A shows the distribution of PSUs in the 2006 and 2010 survey waves depending on which banks were close in 2006. As we want to explore the branch expansion of ProCredit bank between 2006 and 2010 we are primarily interested in the PSUs which are not close to ProCredit in 2006.¹⁴ Our analysis is focused on the 100 PSUs (forty-seven in the 2006 wave and fifty-three in the 2010 wave) that were already close to a RB branch in 2006 but not close to a ProCredit branch. Panel B of [Table II](#) shows that among these 100 PSUs fifty-four are close to ProCredit in 2010, while forty-six remain distant from ProCredit. The comparison of the households in these two sets of PSUs allows us to estimate the additional effect of a new ProCredit branch on households' use of bank accounts given that these households have already access to at least one RB.

As shown in [Table II](#), there are also 151 PSUs (seventy-seven observed in 2006 and seventy-four observed in 2010) which are not close to ProCredit and also not close to a RB in 2006. However, only thirteen of these PSUs are close to a RB branch by 2010, while only three are close to a ProCredit branch by 2010. Thus, it seems that those regions which are

largest retail banks in each country because historical branch opening or location information is not available for all banks. For Macedonia, we resort to the largest three retail banks because they already cover around 50% of the bank branches in the country.

- 14 We observe 170 PSUs (76 in the 2006 survey wave and 94 in the 2010 wave) that were already close to a ProCredit branch in 2006. All of these PSUs were also close to a retail bank branch in 2006.

Table II. Proximity of PSUs to ProCredit and RB branches in 2006 and 2010

This table shows the number of PSUs by the proximity to ProCredit branches and RB branches and by the year of the LITS survey (2006 or 2010). Closeness of bank branches is defined by 5 km thresholds. Panel A shows the number of PSUs by RBs close in 2006 or ProCredit close in 2006 (for both LITS 2006 and LITS 2010 observations). Panel B shows the number of PSUs and the number of households (in parentheses) by ProCredit close in 2010 for all PSUs where at least one RB branch and no ProCredit branch was close in 2006 (for both LITS 2006 and LITS 2010 observations). Definitions and sources of all variables are provided [Table AII](#) in the Appendix.

Panel A: Number of PSUs by proximity to RBs or ProCredit in 2006

		ProCredit close in 2006		LITS wave
		No	Yes	
RBs close in 2006	No	74	0	2010
		77	0	2006
	Yes	53	94	2010
		47	76	2006

Panel B: Number of PSUs (and households) by proximity to ProCredit in 2010 among those close to RBs but not close to ProCredit in 2006

		ProCredit close in 2010		LITS wave
		No	Yes	
RBs close in 2006	Yes	21	32	2010
		(402)	(622)	
		25	22	2006
		(500)	(440)	

not served by either bank type in 2006 are also not served in 2010. These PSUs provide no variation that we could exploit in our empirical analysis.

5. Where Does ProCredit Locate New Branches?

In this section, we examine the first hypothesis derived from our theoretical model: We study whether ProCredit is more likely to open new branches in regions with a larger economically active population and a higher share of low-income households.

5.1 Methodology

We conduct our analysis of the location effect at the PSU level, focusing on the 100 PSUs which were close to a RB, but not close to ProCredit in 2006 (see [Table II](#)). For these 100 locations we estimate the probability of ProCredit opening a new branch by 2010:

$$\text{ProCredit close in 2010}_{e, \text{PSU}} = \alpha_c + \beta_1 \cdot \text{ECONPOP}_{\text{PSU}} + \beta_2 \cdot \text{LOWINCOME}_{\text{PSU}} + \beta_3 \cdot X_{\text{PSU}} + \varepsilon_c.$$

(5)

In Model (5) there are two coefficients of primary interest: β_1 captures the relation between the economically active population in the PSU ($\text{ECONPOP}_{\text{PSU}}$) and the

location decision of ProCredit. Coefficient β_2 captures the relation between the share of low-income households in the PSU ($\text{LOWINCOME}_{\text{PSU}}$) and the location decision of ProCredit.

A key challenge to estimating Model (5) is to obtain accurate measures of our two main explanatory variables: the economic active population and the share of low-income households for the 100 locations (PSUs) we are studying.

As a proxy for local economic activity we use the light intensity at night in the area where each PSU is located. This proxy is based on Henderson, Storeygard, and Weil (2011, 2012) who show that satellite nightlights data are a useful measure for economic activity in geographic regions where national accounts data are of poor quality or unavailable. The nightlight indicator is measured on a scale ranging from 0 to 63, whereby a greater value indicates higher light intensity. Matching on the geographic coordinates for the 100 PSUs in our sample we calculate the average nightlight intensity around each location for each year over the period 2002–10.¹⁵ We employ two indicators of nightlight in Model (5): Nightlight 2006 captures the nightlight intensity and thus level of economic activity and population density in 2006, while $\Delta\text{Nightlight}$ (2010–2006) captures the increase in nightlight intensity and thus the increase in economic activity and population density in the location between 2006 and 2010. With these two indicators we can disentangle whether ProCredit locates new branches in regions which already have a large economically active population in 2006 or in regions where the population and economic activity grows faster over our observation period. Our Supplementary Material illustrates the nightlight intensity data for our four countries, as measured in 2010.

In our sample, the nightlight intensity ranges from 0 in very remote and unpopulated areas to sixty-three in the respective capitals and economic hubs. Figure 1 (first graph) depicts the average nightlight intensity over the period 2002–10 for the fifty-four PSUs where ProCredit opens a new branch between 2006 and 2010 and for the forty-six PSUs where it does not. The figure suggests that the level of economic activity is substantially higher in areas where ProCredit opens a new branch. The figure, however, also suggests that the difference in economic activity for regions where ProCredit locates new branches compared with where it does not is constant over our observation period (and even well before our period). This visual inspection provides a first indication that the location decision of ProCredit is based on the level rather than the dynamics of economic activity.

- 15 Our data come from the Version 4 DMSP-OLS Nighttime Lights Time Series using satellite F15 for years 2002–03, satellite F16 for years 2004–09, and satellite F18 for year 2010. Elvidge et al. (2009), Henderson, Storeygard, and Weil (2011, 2012), and Cauwels, Pestalozzi, and Sornette (2014) provide detailed descriptions of the nightlight data and the process how it is derived from the satellite images produced by the US Airforce Defense Meteorological Satellite Program. See also <http://ngdc.noaa.gov/eog/>. Since our nightlight data come from different satellites over time and different satellites had different sensor settings, it is important to intercalibrate the nightlight data. Elvidge et al. (2009) point out that the value shift between different satellites is not linear but needs a second order adjustment. Therefore, including year and satellite fixed effects is not enough to correct for the value shifts and make the nightlight data comparable over time. We obtain the 2002–09 parameters from Elvidge et al. (2014) and follow the regression-based calibration process suggested by Elvidge et al. (2009) to calculate the 2010 parameters. Nightlight 2006 (Nightlight 2010) is then measured as the average of the nightlight intensity parameters in a radius of 9 km around any geo location.

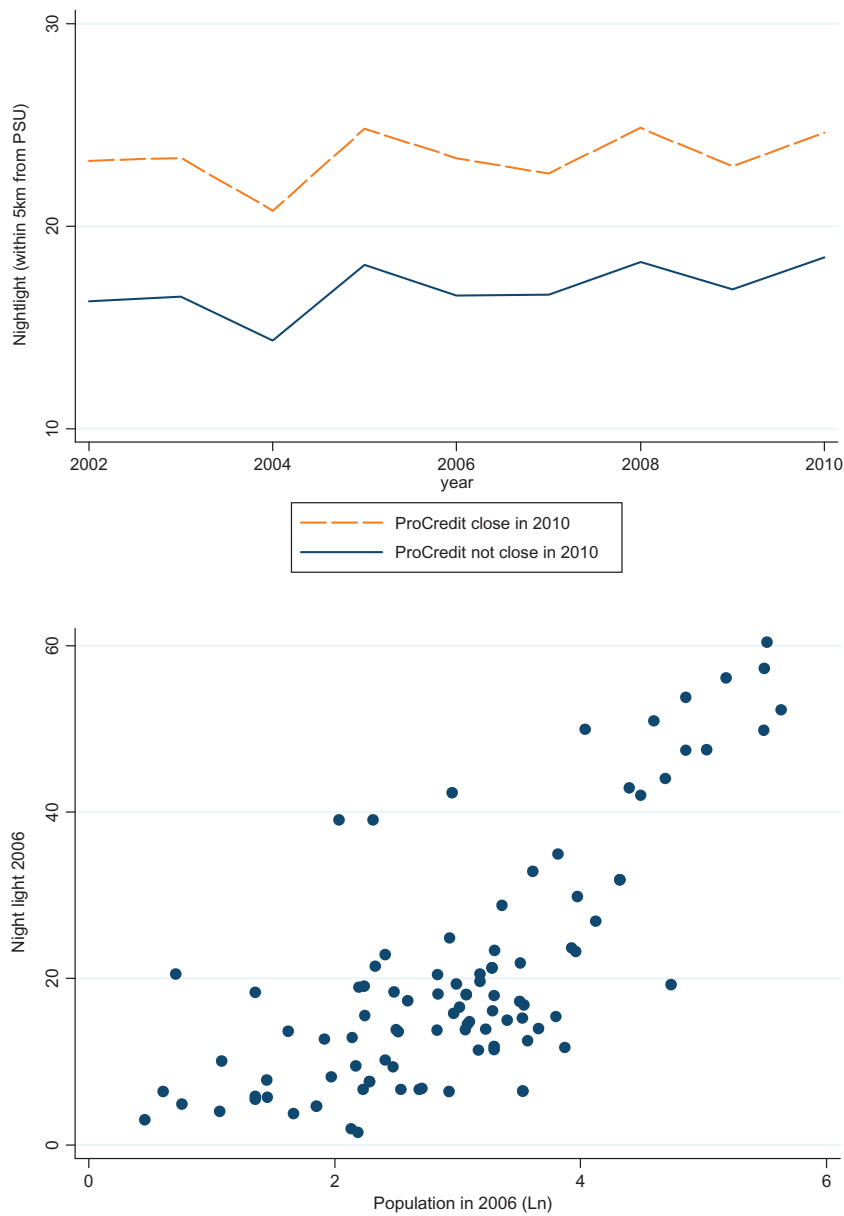


Figure 1. Night light intensity, population density, & RB branches. The figure visualizes summary statistics for the variables capturing night light intensity, population density, and the number of RB branches per PSU for the sample of PSUs which are close to RBs in 2006 and 2010 but not close to ProCredit in 2006. The first graph displays night light intensity over the period 2002–10 distinguishing between PSU in which ProCredit locates between 2006 and 2010 and PSU where ProCredit is not pre-set in 2010. The second graph displays the correlation between night light intensity in 2006 and population density in 2006. The third graph displays the number of bank branches distinguishing between PSU in which ProCredit locates between 2006 and 2010 and PSU where ProCredit is not close in 2010. The proximity of a PSU to RB/ProCredit branches is defined based on 5 km thresholds. Definitions and sources of the variables are provided in Table AII in the Appendix.

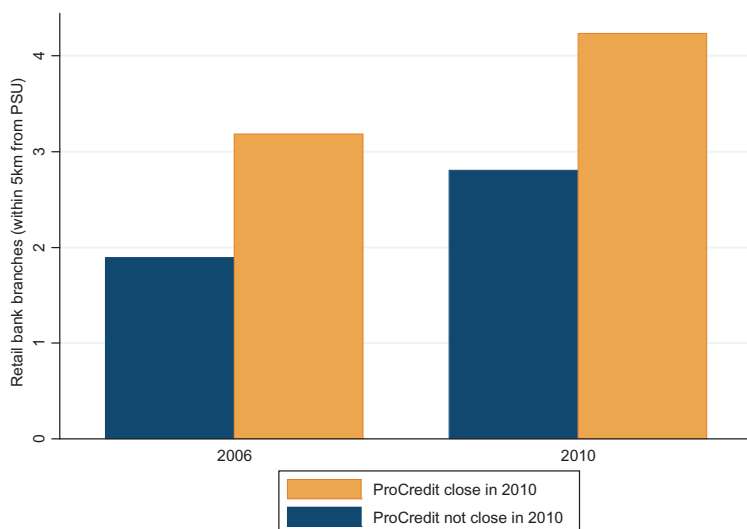


Figure 1. Continued.

Recent evidence suggests that—in a cross-country context—the accuracy of nightlight imagery as a proxy of economic activity depends strongly on the structure of economic activity and the urban–rural population distribution (Ghosh et al., 2010). In particular, nightlight imagery has been shown to be a less precise indicator for economic activity in regions with a substantial share of agricultural production and rural population. Following Ghosh et al. (2010) we therefore employ additional measures of the population density for each PSU in our sample provided by the LandScan database.¹⁶ The variable Population 2006 (Ln) captures the natural logarithm of the population estimate for a radius of 9 km around the geographic coordinate of a PSU. The variable D.Population (2010–2006) is a dummy variable which takes on the value 1 if the within-country ranking of the PSU in terms of population estimate increased between 2006 and 2010.¹⁷

Figure 1 (second graph) shows that in our sample the level of economic activity in 2006 and the population density in 2006 are highly correlated: The pairwise correlation between Nightlight 2006 and Population 2006 (Ln) is 0.75 ($n = 100$, $P < 0.01$). In our baseline estimates of Model (5), we therefore enter the indicators Nightlight 2006 and Population 2006 (Ln) alternatively as measures of the level of the economically active population. In robustness tests, we include Population 2006 as well as the variable Nightlight 2006 (orthogonalized), i.e., the error terms of a regression of $\text{Nightlight } 2006_{\text{PSU}} = \alpha + \beta \cdot \text{Population } 2006_{\text{PSU}} + \epsilon_{\text{PSU}}$. We do this to examine whether controlling for population density, non-agricultural production—which would be captured by Nightlight 2006 (orthogonalized)—has an impact on the location decision of ProCredit. The change in economic activity between

16 The LandScan database provides an estimate of the local population based both on spatial analysis and remote imagery data. For details see: <http://web.ornl.gov/sci/landscan/>.

17 Our indicator of changes in population estimates over time is based on within-country rankings per period as the quantitative population estimates provided by LandScan are not well comparable over time.

2006 and 2010 is hardly correlated with our measure of the change in (relative) population density: The mean (standard deviation) of *D.Nightlight* (2010–2006) is 1.57 (2.62) for PSUs with *D.Population* (2010–2006) = 1 and 1.50 (3.25) for PSUs with *D.Population* (2010–2006) = 0.

Our indicator of the share of low-income households in each location is directly taken from the LITS survey. For each household from each survey wave we obtain an estimate of annual income based on annual expenses data (OECD equivalized per capita). A household is defined as a Low-income household (Middle-income household, High-income household) if it is in the lowest (intermediate, upper) tercile of the income distribution for the respective country in that survey wave.¹⁸ The upper threshold for the first income tercile ranges from 1,141 USD (Bulgaria in 2006) to 2,864 USD (Serbia in 2010). The lower threshold for the third income tercile ranges from 2,160 USD (Bulgaria in 2006) to 4,536 USD (Serbia in 2010). For each PSU we calculate the Share of low-income households as the fraction of the surveyed households in that PSU which are low-income households. The variables Share of middle-income households and Share of high-income households are calculated accordingly.

Our hypothesis for the location effect suggests that we should find a positive relation between our indicators of population and economic activity (*Nightlight* 2006, *D.Nightlight* (2010–2006), *Population* 2006 (Ln), *D.Population* (2010–2006)) and our dependent variable *ProCredit* close in 2010. In addition, we should find a positive relation between Share of low-income households and *ProCredit* close in 2010. However, even if we do observe the expected positive correlations, endogeneity concerns imply that these may not be interpreted in the causal manner suggested by our location hypothesis. In particular, our estimates are likely to be plagued by omitted variable bias: other characteristics of the PSUs in our sample may trigger the location decision of *ProCredit* and these characteristics may be correlated with economic activity, population density, and the share of low-income households.

We add a vector of PSU-level control variables X_{PSU} to our regression Model (5) in order to mitigate concerns about omitted variable bias. Our main control variables capture the structure of economic activity within a PSU. These indicators are taken from the LITS survey data: Each household reports whether its major source of household income is Wage income, whether it is mainly Self-employed or whether it relies mainly on Transfer income. Based on these individual responses we calculate the share of households in a PSU which report that wage employment is their main income source (Share wage income per PSU). Likewise we calculate the share of households that reports that self-employment is their main income source (Share self-employed per PSU).

We further control for the number of RB branches operating in a location. Note that our sample only includes PSUs which are already close to a RB in 2006. However, within this sample the number of RBs close to a PSU in 2006 (Number of RBs in 2006) as well as the change in this number between 2006 and 2010 (*D.Number of RBs* (2010–2006)) varies strongly. We control for both variables in order to account for the fact that

18 The tercile thresholds are given by the following values of Income per country and wave (measured in ln(USD)): Albania 2006: 7.326 (33.33%), 7.874 (66.67%)/2010: 7.568 (33.33%), 8.098 (66.67%); Bulgaria 2006: 7.048 (33.33%), 7.678 (66.67%)/2010: 7.750 (33.33%), 8.220 (66.67%); Macedonia 2006: 7.290 (33.33%), 7.834 (66.67%)/2010: 7.852 (33.33%), 8.308 (66.67%); Serbia 2006: 7.454 (33.33%), 8.027 (66.67%)/2010: 7.976 (33.33%), 8.422 (66.67%).

Table III. Location effect

This table shows the estimates of a linear probability model where the dependent variable is ProCredit close in 2010. The parameters are estimated for PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006. PSU control variables are Share of middle-income households, Share wage income per PSU, and Share self-employed per PSU. Observations are on the PSU level. Ordinary standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in Table All in the Appendix.

Sample	(1)	(2)	(3)	(4)	(5)
	PSUs close to RBs in 2006 and 2010 and not close to ProCredit in 2006				
Dependent variable	ProCredit close in 2010				
Nightlight 2006	0.011*** [0.004]				
D.Nightlight (2010–2006)	0.002 [0.020]		0.003 [0.020]	0.006 [0.019]	0.018 [0.019]
Population 2006 (Ln)		0.128*** [0.042]	0.131*** [0.041]	0.124*** [0.043]	0.042 [0.057]
D.Population (2010–2006)		0.074 [0.100]	0.060 [0.105]	0.065 [0.104]	0.053 [0.100]
Nightlight 2006 (orthogonalized)			0.004 [0.007]	0.007 [0.007]	0.004 [0.007]
Rural				−0.153 [0.115]	−0.106 [0.112]
Nightlight 2006 (orthogonalized) *				−0.015 [0.013]	−0.014 [0.013]
Rural					
Number of RBs in 2006					0.068** [0.030]
D.Number of RBs (2010–2006)					0.034 [0.037]
Share of low-income households	0.690*** [0.242]	0.509** [0.229]	0.581** [0.257]	0.576** [0.261]	0.663** [0.264]
PSU controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	100	100	100	100	100
Number of PSUs	100	100	100	100	100
Mean of dependent variable	0.54	0.54	0.54	0.54	0.54
R ²	0.234	0.248	0.253	0.274	0.326
Method	OLS	OLS	OLS	OLS	OLS

ProCredit may just be opening up new branches where other banks are also opening up new branches. Figure 1(third graph) documents that the decision of ProCredit to open new branches between 2006 and 2010 decision is strongly related to Number of RBs in 2006, but hardly to D.Number of RBs (2010–2006). Finally, we add country fixed effects α_c to account for differences in the economic and regulatory environment across the four countries in our sample.

5.2 Results

Table III presents multivariate results for the location effect. The specifications presented in Columns (1–4) all include our main variable Share of low-income households and an indicator of economic activity/population density. The four specifications differ, however, in how we account for economic activity and population density during our observation period, and which PSU-level control variables we include. All models are estimated with a linear probability model.¹⁹

In Column (1) of **Table III** we control for population density and economic activity with our nightlight indicators (Nightlight 2006, D.Nightlight (2010–2006)) only. In Column (2) we replace these indicators with our measures of the local population density (Population 2006, D.Population (2010–2006)). In Column (3) we enter Population 2006, D.Population (2010–2006), D.Nightlight (2010–2006), as well as Nightlight 2006 (orthogonalized). This specification allows us to examine whether—for a given population density—non-agricultural economic activity affects the location decision of ProCredit. Column (4) provides a robustness test of Column (3) examining whether non-agricultural economic activity plays a more important role for the location decision of ProCredit in rural versus urban areas. To this end we add the dummy variable Rural (which is 1 for non-urban PSUs) and the interaction term Nightlight 2006 (orthogonalized) * Rural. The Column (1)–(4) models all include PSU-level control variables for the level and sources of regional income: Share of middle-income households, Share wage income per PSU, Share self-employed per PSU. In Column (5) we add our control variables Number of RBs in 2006 and D.Number of RBs (2010–2006) to examine whether ProCredit locates where economic activity is high, or whether the bank just follows other banks.

In line with our location hypothesis **Table III** results suggest that between 2006 and 2010 ProCredit is more likely to open a new branch in locations with a high Share of low-income households. The economic magnitude of this location effect is sizeable: Column (1)–(5) estimates suggest that a one standard deviation increase in the share of low-income households (0.22) increases the probability of ProCredit entering a location by 11–15 percentage points.

In line with our location hypothesis (and as illustrated by **Figure 1**) **Table III** results also suggest that ProCredit opens new branches in regions which already have a large, economically active population in 2006. In Column (1) we obtain a statistically and economically significant effect of Nightlight 2006: A one standard deviation increase in nightlight intensity (roughly 18 units) increases the probability of ProCredit opening a branch by 20 percentage points. Similarly, the estimate for Population 2006 (Ln) in Column (2) suggests that a one standard deviation increase in the population density (1.15) increases the probability of ProCredit opening a branch by 15 percentage points. These estimated effects are large compared with the unconditional probability of ProCredit opening a branch in 1 of the 100 PSUs in our sample (54%). By contrast the small and insignificant estimates for D.Nightlight (2010–2006) in Column (1) and D.Population (2010–2006) in Column (2) suggest that the location decision of ProCredit is not significantly related to the change in local economic activity or population density over our observation period. The Column (3)–(4) results show that our main findings for the location effect as presented in Column (2) are robust to accounting for potential effects of agricultural versus non-agricultural activity.

19 In unreported tests we confirm that our results are robust to using a non-linear (probit) estimation method.

Column (5) estimates in Table III, however, cast some doubt on a causal interpretation of the observed relation between the location decision of ProCredit and the level of economic activity in a PSU (Nightlight 2006, Population 2006 (Ln)). In this model we control for the level and the change in the number of other banks operating in each location. The results show that the location decision of ProCredit is strongly correlated with Number of RBs in 2006: A one standard-deviation increase in Number of RBs in 2006 (11.5) increases the probability of ProCredit opening a branch by 78 percentage points. By contrast, the coefficient of Population 2006 (Ln) loses economic and statistical significance, once we control for the number of other bank branches operating in an area. There are two interpretations of the finding: On the one hand, the location decision of ProCredit may be primarily driven by a strategy of following other banks, rather than of locating in areas with a large, economically active population. On the other hand, the number of other bank branches located in an area may simply be a better indicator of local economic activity than nightlight imagery and local population estimates. In this case, Column (5) results would support our location hypothesis that ProCredit does locate in economically active areas.

6. What Is the Impact of ProCredit on Financial Inclusion?

In this section we examine whether—as suggested by our second hypothesis—the opening of a ProCredit branch in a location increases the number of banked households, and whether this effect is particularly strong among low-income households.

6.1 Methodology

To estimate the impact of ProCredit on financial inclusion we conduct a household-level analysis. We use a difference-in-difference framework that compares the use of bank accounts by a treated group of households (those in locations where ProCredit opens a new branch between 2006 and 2010) to a control group of households (those in locations where ProCredit does not open a branch between 2006 and 2010).

To estimate the differential effect in the use of bank accounts between the treated and control groups we would ideally observe the same households in 2006 and 2010. The LITS data, however, consist of two repeated cross-sections from which we construct a “pooled” panel sample. To the treated group we assign all households in the fifty-four PSUs that were not close to ProCredit in 2006 but close in 2010. The control group then consists of all households in the forty-six PSUs that were not close to ProCredit in both years. Households that are observed in the 2006 wave serve as the pre-treatment observations, while households observed in the 2010 wave serve as the post-treatment observations. As Panel B of Table II shows, our data provide us with a similar number of pre-treatment and post-treatment observations for both the treated and control groups.

We estimate the volume effect of ProCredit with the following linear difference-in-difference model²⁰:

20 In unreported robustness tests we confirm that our results are robust to using a non-linear (probit) estimation method.

$$\begin{aligned} \text{Account}_{i,\text{PSU},c} = & \alpha_c + \beta_1 \times \text{LITS 2010} + \beta_2 \times \text{ProCredit close in 2010}_{\text{PSU}} \\ & + \beta_3 \times \text{LITS 2010} * \text{ProCredit close in 2010}_{\text{PSU}} + \beta_4 \times X_i + \beta_5 \times Z_{\text{PSU}} + \varepsilon_{\text{PSU}}. \end{aligned} \quad (6)$$

In Model (6) the coefficient β_1 captures the increase in account use in the control group. The coefficient β_2 captures the pre-treatment difference in account use (i.e., among households observed in 2006) between the treatment and control group. The coefficient β_3 for the interaction term $\text{LITS 2010} * \text{ProCredit close in 2010}_{\text{PSU}}$ is our effect of interest in this model. This coefficient captures the difference-in-difference effect in account use between the 2006 and 2010 households comparing the treatment group to the control group. We expect this coefficient to be positive and significant if a new ProCredit branch leads to an increase in the share of banked households (volume effect). Moreover, we expect this coefficient to be especially strong in the subsample of low-income respondents if, as suggested by our model, MFBs foster financial inclusion of low-income households (composition effect).

The identification of the difference-in difference effect crucially depends on the common trend assumption which implies that the increase in bank account use would have been the same in the treatment and control groups in the absence of treatment (i.e., if ProCredit had not opened new bank branches). Unfortunately, we have neither household-level nor PSU-level information on the financial inclusion of households in our sample prior to 2006. Thus, we cannot test the common trend assumption using pre-treatment information (under the assumption that pre-treatment would have behaved the same way as after the treatment). We resort to controlling for all household and PSU characteristics which may affect the use of bank accounts by households in the pre-treatment and post-treatment observations of the treatment and control groups.

The vector of household controls X_i accounts for differences in household characteristics between the treatment and control households, in both the pre-treatment observations (2006 LITS wave) and the post-treatment observations (2010 LITS wave). We employ control variables to capture variation in household demand for financial services as well as the transaction costs of using these services. The variable Income measures annual household expenses (in log USD),²¹ while the income source of a household is captured by the dummy variables Wage income and Self-employed. University degree indicates whether the respondent has tertiary-level education. We also include Household size, as well as the Age and gender (Female) of the household head. The variables Language and Muslim are measures of social integration.²² We further control for the ownership of a Car, Computer, or Mobile phone as well as Internet access of the household. These indicators account for differences in the transaction costs of using a bank account, but may also be related to economic activity and household income.

Our analysis in Section 5 documented that the decision of ProCredit to open a new branch is non-random. In estimating Model (6) we are therefore confronted with a potential omitted variable bias: Between 2006 and 2010 ProCredit may have opened branches in locations which experienced structural developments which would have led to an increase

21 Income is equalized at the OECD scale to account for the varying number of adults and children across households.

22 Muslim respondents may also be reluctant to use commercial banking services for religious reasons. Using the LITS 2006 data Grosjean (2011) provides evidence that regions in South-East Europe which were under the influence of the Ottoman Empire show a lower level of financial development.

in the use of bank accounts (for households with a given socioeconomic profile X_i) even if ProCredit did not locate there. For example, improvements in the infrastructure (better roads, public transport) may have reduced the transaction costs of using a bank account (for all households) and also encouraged ProCredit to locate in a region. Also, changes in the structure of local income sources (e.g., more inward remittance transfers from migrant family members) may have encouraged the use of bank accounts through network effects and also encouraged ProCredit to locate in a region.

We mitigate concerns about omitted variables by including a vector Z_{PSU} of PSU-level control variables already employed in our analysis of the location effect. To be precise we control for all PSU-level characteristics which are included as explanatory variables in Column (4) of Table III. Most noteworthy among these PSU-level controls are the level and the change in the number of RB branches in the PSU, Number of RBs (2006), and D.Number of RBs (2010–2006). We would expect that any structural development in a location that would lead to an increase in the use of bank accounts—in the absence of ProCredit—would be associated with a stronger presence of ordinary RBs in that location. The variables Number of RBs (2006) and D.Number of RBs (2010–2006) thus provide us with indicators of the level and change in the attractiveness of each PSU for banks and directly address the endogeneity concerns alluded to above. Finally, we use country fixed effects α_C , or alternatively regional fixed effects α_R , to account for aggregate differences in economic conditions which may have affected the use of bank accounts.²³

6.2 Results

Table IV, Columns (1)–(3) present our difference-in-difference estimates for the volume effect based on Model (6). In Column (1) we control for differences in household characteristics and country fixed effects. In Column (2) we replace country fixed effects with regional fixed effects. In Column (3) we add our vector of PSU-level control variables to the Column (1) specification. The explanatory variable of main interest is the interaction term $LITS_{2010} * ProCredit_{close\ in\ 2010}$. It captures the difference-in-difference effect and reports the differential increase in the use of bank accounts between 2006 and 2010 for households in areas where ProCredit opens a new branch versus households in areas where ProCredit does not open a branch.

Table IV documents a strong increase in account use in PSUs where ProCredit opens new branches compared with PSUs where it does not. Controlling for differences in socioeconomic characteristics across households in Columns (1) and (2) the estimated difference-in-difference effect of a new ProCredit branch ($LITS_{2010} * ProCredit_{close\ in\ 2010}$) is 16–18 percentage points. Both estimates are significant at the 10% level. In Column (3) we find that controlling for differences in socioeconomic conditions between treated and untreated PSUs strengthens our estimate both in statistical and economic terms: Households in PSUs where ProCredit opens a branch display a 21 percentage point higher increase in account use than households in PSUs where ProCredit does not locate. By comparison the aggregate increase in account use in our sample between 2006 and 2010 is 25 percentage points (see Table I).²⁴

23 The regional fixed effects are based on the NUTS 2 level classification. A more granular classification (e.g., NUTS 3) is not feasible in our analysis due to the lack of sufficient within-region observations.

24 In unreported robustness tests we establish that the difference-in-difference effect estimated in Table IV is not driven by one particular country in our sample. To this end we replicate the analysis

Table IV. Volume effect and composition effect

This table displays the estimates of a linear probability model where the dependent variable is Account. The parameters are estimated for households located in PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006. Household control variables are Income, Wage income, Self-employed, University degree, Household size, Age, Female, Language, Muslim, Car, Computer, Mobile phone, Internet. PSU control variables are D.Nightlight (2010–2006), Nightlight 2006 (orthogonalized), Population 2006 (Ln), D.Population (2010–2006), Rural, Nightlight 2006 (orthogonalized) * Rural, Average income per PSU, Share wage income per PSU, Share self-employed per PSU, Number of RBs in 2006, and D.Number of RBs (2010–2006). Region FE corresponds to NUTS 2 regions per country. Observations are on the household level. Standard errors are clustered on the PSU level and are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in Table AII in the Appendix.

Sample	(1)	(2)	(3)	(4)	(5)	(6)
	PSUs close to RBs in 2006 and not close to ProCredit in 2006					
Households	All households			Low-income households	Middle-income households	High-income households
Dependent variable	Account	Account	Account	Account	Account	Account
LITS 2010	0.069 [0.073]	0.085 [0.074]	0.066 [0.077]	0.072 [0.092]	0.084 [0.106]	0.049 [0.105]
ProCredit close in 2010	0.004 [0.058]	0.005 [0.054]	−0.029 [0.055]	−0.02 [0.056]	−0.023 [0.061]	−0.015 [0.085]
LITS 2010 * ProCredit close in 2010	0.179* [0.091]	0.160* [0.094]	0.210** [0.091]	0.216** [0.103]	0.212** [0.103]	0.144 [0.118]
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
PSU controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	No	No
Country FE	Yes	No	Yes	Yes	Yes	Yes
Observations	1,954	1,954	1,954	600	708	646
Number of PSUs	98	98	98	98	98	96
Mean of dependent variable	0.49	0.49	0.49	0.38	0.49	0.58
R ²	0.249	0.260	0.275	0.279	0.296	0.262
Method	OLS	OLS	OLS	OLS	OLS	OLS

The results in Table IV provide evidence of a significant volume effect induced by the expansion of the ProCredit Bank branch network between 2006 and 2010. Our theoretical model suggests that given the presence of a RB in all of the regions where ProCredit expanded this volume effect should be mostly attributed to low-income households. In Table

dropping (in separate analyses) each of the four countries. Due to the lower and varying number of observations our estimates vary in economic magnitude and precision but remain qualitatively robust. We also examine whether our estimates are impacted by the composition of retail banks (foreign-owned versus domestic-owned) close to a PSU. We add a variable Foreign share of retail banks (2006) and the interaction term Foreign share of retail banks (2006) * ProCredit close in 2010 to Column (3) in Table IV. We find that the estimated coefficient for our difference-in-difference effect of ProCredit is unaffected by these additional control variables.

IV, Columns (4)–(6) we examine which households benefit most from the expansion of the ProCredit branch network. We replicate our analysis from Column (3) of Table IV for three subsamples of households: low-income, middle-income, and high-income households.²⁵

Table IV, Column (4)–(6) results document that our difference-in-difference estimate of the effect of ProCredit is especially strong for the low- and middle-income households. Our estimates for the low-income subsample in Column (4) as well as for the middle-income sample in Column (5) are statistically significant and similar in economic magnitude (21 percentage points) to our full sample results in Column (3). By contrast the estimate for the high-income sample in Column (6) is weaker in terms of economic magnitude (14 percentage points) and is statistically insignificant.

While the absolute magnitude of our difference-in-difference estimate is larger for low- and middle-income households than for high-income households statistical tests cannot reject equality of the subsample estimates.²⁶ However, a comparison of the relative magnitude of our estimates underscores the substantial differences in the effect of a new ProCredit branch across income groups. The share of banked households is 38% among our low-income subsample. Relative to this share the point estimate of our difference-in-difference effect in this subsample (21.6 percentage points) would imply an increase in the share of banked households by 55%. By comparison, the relative increase in the share of banked households suggested by our estimates is 43% for middle-income households and only 25% for high-income households. Thus, our estimates for the relative impact of a new ProCredit branch on the share of banked households is more than twice as large for low-income households than it is for high-income households. Taken the above results together, the heterogeneous treatment effects observed across income groups in Table IV provide indicative support to our conjecture that the volume effect of new MFB branches may go hand in hand with a composition effect: Low-income households may benefit most.

In Table V we explore further potential heterogeneities in the impact of a ProCredit branch on financial inclusion across different household types. In all seven columns of the table we replicate our preferred specification from Table IV (Column 3) for different subsamples of households. In Columns (1) and (2) we split our sample by the gender of the household head. In Columns (3) and (4) we split our sample by the age of the household head (above or below the median age of 54 years). Finally, in Columns (5)–(7) we split our

25 Note that in our low-income sample we include not only the Type 2 households from our model but also the Type 1 households which are too poor to open an account at any bank. Thus, we will yield conservative estimates for the impact of the microfinance bank on the bankable low-income households (Type 2).

26 We conduct two types of tests to establish whether our difference-in-difference estimate differs significantly across income groups. First, we pool the subsamples of low-income and high-income households and estimate Model (6) including the triple interaction term Low income * LITS 2010 * ProCredit close in 2010 and in order to saturate the model the interaction terms Low income * LITS 2010 and Low income * ProCredit close in 2010. The estimated triple interaction term is positive, but imprecisely estimated (point estimate: 0.047, standard error: 0.111). Second, we simultaneously run the two regressions in Columns (4) and (6) and then use a "Chow" test to test for differences in the estimated difference-in-difference parameter LITS 2010 * ProCredit close in 2010 across the two subsamples. The test statistic ($p=0.51$) does not reject equality across the two subsamples.

Table V. Volume effect by household head characteristics

This table displays the estimates of a linear probability model where the dependent variable is Account. The parameters are estimated for households located in PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006. Household control variables are Income, Wage income, Self-employed, University degree, Household size, Age, Female, Language, Muslim, Car, Computer, Mobile phone, Internet. PSU control variables are D.Nightlight (2010–2006), Nightlight 2006 (orthogonalized), Population 2006 (Ln), D.Population (2010–2006), Rural, Nightlight 2006 (orthogonalized) * Rural, Average income per PSU, Share wage income per PSU, Share self-employed per PSU, Number of RBs in 2006, and D.Number of RBs (2010–2006). Observations are on the household level. Standard errors are clustered on the PSU level and are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in Table AII in the Appendix.

Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PSUs close to RBs in 2006 and not close to ProCredit in 2006						
Household head	Male	Female	Below median age	Above median age	Wage income	Self-employed	Transfer income
Dependent variable	Account	Account	Account	Account	Account	Account	Account
LITS 2010	0.068 [0.077]	0.039 [0.128]	0.119 [0.090]	0.031 [0.080]	0.026 [0.098]	0.065 [0.114]	0.090 [0.083]
ProCredit close in 2010	−0.007 [0.059]	−0.111 [0.074]	0.032 [0.067]	−0.116* [0.063]	−0.022 [0.066]	0.118 [0.115]	−0.115** [0.056]
LITS 2010 * ProCredit close in 2010	0.219** [0.099]	0.205* [0.112]	0.141 [0.100]	0.262*** [0.100]	0.182* [0.106]	0.095 [0.171]	0.289*** [0.097]
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PSU controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,479	475	1,011	943	928	312	714
Number of PSUs	98	90	98	98	98	79	98
Mean of dependent variable	0.48	0.52	0.52	0.45	0.57	0.47	0.39
R ²	0.265	0.343	0.281	0.308	0.316	0.282	0.293
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS

sample by the main income source of the household: wage income, self-employment, or transfer income (among which the overwhelming majority are pensions).

The column (1)–(2) results suggest no gender difference in the effect of ProCredit on the use of bank accounts. By contrast we find that the impact of ProCredit on financial inclusion does differ by household age and by primary income source. The Column (3)–(7) results show that the difference-in-difference estimate is particularly large for older households (26 percentage points compared with 14 percentage points for younger households) and for households that receive transfer income (29 percentage points compared with 18 percentage points for receivers of wage income and 10 percentage points for the self-employed). Statistical tests cannot reject the equality of the

difference-in-difference estimates by household age or income source.²⁷ However, again the size of the ProCredit effect appears much stronger for older households and those that receive transfer income when comparing the point estimates to the respective subsample shares of banked households. For example the point estimate for households that rely on transfer income (0.289) amounts to 74% of the share of banked households (0.39) in this subsample. By comparison, the point estimate for households that rely on wage income (0.182) amounts to only 33% of the share of banked households (0.57) in this subsample.

Table V results point to an interesting result: In South-East Europe ProCredit seems to have fostered the financial inclusion of a specific demographic group which appears to be underserved by ordinary RBs: elderly households. This result is supported by statements of ProCredit senior management suggesting that ProCredit actively targeted elderly people in South-East Europe who had some savings but no account to help them open a formal account in which to deposit their pensions and to provide them with a way to save for their (grand-)children.²⁸

The finding that elderly households may be particularly inclined to open an account with a development orientated MFB is in line with the composition effect suggested by our theoretical model: For older households the simple and transparent products provided by MFBs may imply lower non-financial costs of opening and maintaining an account compared with a regular RB. The heterogeneous treatment effects by household income source also support the conjecture that MFBs encourage financial inclusion among households with stronger “cultural barriers” to RBs.

In Table VI we examine whether the expansion of the ProCredit branch network in South-East Europe had an impact on households beyond their use of bank accounts. This analysis is motivated by Bruhn and Love (2014) who show that improved access to financial services can have pronounced effects on real economic outcomes for low-income households. They study the expansion of Banco Azteca in Mexico and show that in regions where Azteca opened up a branch low-income households experienced a decline in unemployment and an increase in income.

Our conjecture is that the expansion of ProCredit in South-East Europe is unlikely to be associated with similar effects on household income and employment. The reason is that one of the key services of Banco Azteca is to provide credit for durable goods purchases to households and entrepreneurs, whereas ProCredit focuses mainly on providing savings services to households. We therefore expect that household clients of ProCredit are most likely to use payment and savings services to accommodate their existing streams of income and expenses rather than to alter their economic activities. This conjecture is further supported by Table V finding that the impact of ProCredit on financial inclusion is strongest among older households and receivers of transfer income.

Table VI results confirm our expectations: A ProCredit branch has no differential effect on the likelihood of households to use bank cards or to own durable consumption goods. Moreover, ProCredit has no differential effect on income levels or income sources of households. In Table VI we replicate our preferred model from Table IV

27 We simultaneously run the regressions in Columns (3)–(4) and (5)–(6) of Table V and then use a “Chow” test to test for differences in the estimated difference-in-difference parameter LITS 2010

* ProCredit close in 2010 across the respective subsamples.

28 This information was provided to the authors by the senior management of ProCredit Holding.

Table VI. Cards and real effects

This table displays the estimates of a linear probability model where the dependent variables are Card, Car, Income, Some self-employed, Some wage income. The parameters are estimated for households located in PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006. Household control variables are University degree, Household size, Age, Female, Language, Muslim, Computer, Mobile phone, Internet. PSU control variables are D.Nightlight (2010–2006), Nightlight 2006 (orthogonalized), Population 2006, D.Population (2010–2006), Rural, Nightlight 2006 (orthogonalized) * Rural, Average income per PSU, Share wage income per PSU, Share self-employed per PSU, Number of RBs in 2006, and D.Number of RBs (2010–2006). Observations are on the household level. Standard errors are clustered on the PSU level and are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in Table AII in the Appendix.

Sample	(1) PSUs close to RBs in 2006 and not close to ProCredit in 2006	(2)	(3)	(4)	(5)
Dependent variable	Card	Car	Income	Some self-employed	Some wage income
LITS 2010	0.054 [0.058]	0.016 [0.033]	0.031 [0.041]	−0.011 [0.041]	−0.017 [0.035]
ProCredit close in 2010	−0.063 [0.048]	0.065* [0.038]	−0.011 [0.028]	−0.021 [0.024]	0.017 [0.028]
LITS 2010 * ProCredit close in 2010	0.110 [0.078]	−0.072 [0.048]	0.043 [0.042]	0.051 [0.040]	−0.029 [0.040]
Household controls	Yes	Yes	Yes	Yes	Yes
PSU controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	1,954	1,954	1,954	1,954	1,954
Number of PSUs	98	98	98	98	98
Mean of dependent variable	0.43	0.47	7.84	0.25	0.59
R ²	0.211	0.256	0.349	0.179	0.260
Method	OLS	OLS	OLS	OLS	OLS

(Column 3), replacing the dependent variable Account with measures of bank card usage, durable consumption, income levels, and sources of income. In Column (1) the dependent variable Card indicates whether any member of the household has a debit or credit card. In Column (2) the variable Car captures whether some member of the household owns a car. In Column (3) the variable Income measures annual household expenses. In Columns (4) and (5) the variables Some self-employment and Some wage income indicate whether the household yields any income from either of these sources. In all columns we find an insignificant coefficient of our difference-in-difference estimator LITS 2010*ProCredit close in 2010.

7. Robustness Checks

7.1 Placebo Test

The analysis so far has shown that the opening of new branches of a commercial MFB can foster financial inclusion beyond what normal RBs do: A ProCredit branch is associated with an increased share of banked households, especially among the low-income and older population.

While our multivariate analysis controlled for the change in the number of RBs located in each PSU, one might still be concerned whether our results are indeed driven by a change in the type of banks operating in a region, e.g., the opening of a MFB branch, as opposed to just an increase in the number of banks competing in a region.

To confirm that our results are institution-specific we replicate our [Table III](#) and [Table IV](#) results replacing ProCredit with a Placebo bank. In each country we choose a Placebo bank which is similar to ProCredit with respect to its foreign ownership, the number of branches in 2006 and the expansion of its branch network until 2010. [Table AI](#) in the Appendix provides information on the chosen banks and their branch networks.²⁹

We conduct our placebo test on households in 88 PSUs which were (i) close to a RB in 2006, (ii) not close to ProCredit in 2006, and (iii) not close to the Placebo banks in 2006. Among these eighty-eight PSUs, the Placebo banks open new branches in thirty-one PSUs between 2006 and 2010.

The multivariate analysis of the Placebo bank's location decision in [Table VII](#) provides evidence that the location decision of the Placebo bank is similar to that of ProCredit: We find that the Placebo bank also opens new branches in areas with higher economic activity in 2006, and also with a higher share of low-income households. [Table VII](#) results suggest that given the presence of established RBs which may already be serving high-income clients, new retail entrants target similar regions as the MFB when they expand their branch networks. However, do these RBs also increase the use of financial services, and foster the financial inclusion of low-income households?

[Table VIII](#) presents the difference-in-difference results for the volume effect (Columns 1–3) and the composition effect (Columns 5–7) of the Placebo bank. In contrast to our results for ProCredit we find no significantly positive coefficient for the difference-in-difference term (LITS 2010 * Placebo bank close in 2010). This suggests that the use of bank accounts does not increase more in areas where the Placebo bank opens a new branch compared with areas where it does not open a new branch. And even though the Placebo bank opens its new branches in areas with a higher share of low-income households, these households do not benefit by experiencing a disproportionate increase in bank accounts.

In Column 4 of [Table VIII](#) we directly test the volume effect of ProCredit against the volume effect of the Placebo bank. To this end we again look at those PSUs that were close to at least one RB in 2006 and 2010 but not close to ProCredit nor close to the Placebo bank in 2006. We then replicate the analysis of Column (3) but jointly estimate the difference-in-difference effect for ProCredit (LITS 2010 * ProCredit close in 2010) and the Placebo

29 In unreported robustness tests we replace the chosen set of Placebo banks with an alternative placebo bank for each country and obtain similar findings.

Table VII. Location effect (Placebo bank)

This table shows the estimates of a linear probability model where the dependent variable is Placebo bank close in 2010. The parameters are estimated for PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006 and no Placebo bank branch was close in 2006. PSU control variables are Share of middle-income households, Share wage income per PSU and Share self-employed per PSU. Observations are on the PSU level. Ordinary standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05 and 0.10, level respectively. Definitions and sources of the variables are provided in [Table All](#) in the Appendix.

Sample	(1)	(2)	(3)	(4)	(5)
	PSUs close to RBs in 2006 and 2010 and not close to ProCredit in 2006 and not close to Placebo bank in 2006				
Dependent variable	Placebo bank close in 2010				
Nightlight 2006	0.007* [0.004]				
D.Nightlight (2010–2006)	–0.039** [0.018]		–0.039** [0.017]	–0.038** [0.018]	–0.039** [0.019]
Population 2006 (Ln)		0.161*** [0.041]	0.158*** [0.041]	0.157*** [0.041]	0.177*** [0.046]
D.Population (2010–2006)		–0.078 [0.100]	–0.062 [0.098]	–0.060 [0.099]	–0.078 [0.097]
Nightlight 2006 (orthogonalized)			–0.008 [0.005]	–0.007 [0.005]	–0.005 [0.005]
Rural				–0.042 [0.099]	–0.029 [0.108]
Nightlight 2006 (orthogonalized) * Rural				–0.004 [0.012]	–0.003 [0.012]
Number of RBs in 2006					0.028 [0.049]
D.Number of RBs (2010–2006)					–0.040 [0.041]
Share of low-income households	0.691** [0.270]	0.497* [0.276]	0.341 [0.287]	0.344 [0.300]	0.353 [0.301]
PSU controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	88	88	88	88	88
Number of PSUs	88	88	88	88	88
Mean of dependent variable	0.35	0.35	0.35	0.35	0.35
R ²	0.170	0.232	0.291	0.293	0.307
Method	OLS	OLS	OLS	OLS	OLS

bank (LITS 2010 * Placebo bank close in 2010). This analysis is feasible because there are significant differences in the expansion pattern of the Placebo banks compared with ProCredit among this same sample of eighty-eight PSU: ProCredit opens a branch in twenty-three locations where the Placebo banks do not, while the Placebo banks open a branch in eight locations where ProCredit does not. Column (4) results confirm our

Table VIII. Volume effect and composition effect (Placebo bank)

This table displays the estimates of a linear probability model where the dependent variable is Account. The parameters are estimated for households located in PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006 and no Placebo bank branch was close in 2006. Household control variables are Income, Wage income, Self-employed, University degree, Household size, Age, Female, Language, Muslim, Car, Computer, Mobile phone, Internet. PSU control variables are D.Nightlight (2010–2006), Nightlight 2006 (orthogonalized), Population 2006 (Ln), D.Population (2010–2006), Rural, Nightlight 2006 (orthogonalized) * Rural, Average income per PSU, Share wage income per PSU, Share self-employed per PSU, Number of RBs in 2006, and D.Number of RBs (2010–2006). Region FE correspond to NUTS II regions per country. Observations are on the household level. Standard errors are clustered on the PSU level and are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in Table AII in the Appendix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	PSUs close to RBs in 2006 and 2010 and not close to ProCredit in 2006 and not close to Placebo bank in 2006						
Households	All households				Low-income households	Middle-income households	High-income households
Dependent variable	Account	Account	Account	Account	Account	Account	Account
LITS 2010	0.218*** [0.063]	0.253*** [0.068]	0.218*** [0.059]	0.110 [0.075]	0.279*** [0.067]	0.236** [0.092]	0.146* [0.087]
Placebo bank close in 2010	−0.004 [0.068]	0.012 [0.063]	−0.084 [0.074]	−0.071 [0.071]	−0.066 [0.072]	−0.182** [0.078]	0.000 [0.112]
LITS 2010 * Placebo bank close in 2010	−0.070 [0.110]	−0.138 [0.114]	−0.043 [0.099]	−0.123 [0.098]	−0.103 [0.106]	0.044 [0.107]	−0.138 [0.147]
ProCredit close in 2010				0.078 [0.061]			
LITS 2010 * ProCredit close in 2010				0.181* [0.098]			
Household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PSU controls	No	No	Yes	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	No	No	No
Country FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Observations	1,712	1,712	1,712	1,712	524	619	569
Number of PSUs	86	86	86	86	86	86	85
Mean of dependent variable	0.48	0.48	0.48	0.48	0.37	0.49	0.58
R ²	0.236	0.252	0.279	0.300	0.301	0.326	0.249
Method	OLS	OLS	OLS	OLS	OLS	OLS	OLS

previous findings. Even when controlling for the branch expansion of the Placebo bank we still find that the opening of a new ProCredit branch leads to a 18 percentage point increase in the share of households with a bank account. In contrast, we again do not find an effect on account use from new Placebo bank branches.

Summarizing, the Placebo bank results provide evidence that it is not the entrance of any additional bank into a region that increases the use of bank accounts in general and among low- and middle-income households in particular. By contrast, the results

Table IX. Volume effect and composition effect (10 km threshold)

This table displays the estimates of a linear probability model where the dependent variable is Account. The parameters are estimated for households located in PSUs where at least one RB branch was close in 2006 and in 2010 and no ProCredit branch was close in 2006 (within 10 km). Household control variables are Income, Wage income, Self-employed, University degree, Household size, Age, Female, Language, Muslim, Car, Computer, Mobile phone, Internet. PSU control variables are D.Nightlight (2010–2006), Nightlight 2006 (orthogonalized), Population 2006 (Ln), D.Population (2010–2006), Rural, Nightlight 2006 (orthogonalized) * Rural, Average income per PSU, Share wage income per PSU, Share self-employed per PSU, Number of RBs in 2006, and D.Number of RBs (2010–2006). Region FE corresponds to NUTS 2 regions per country. Observations are on the household level. Standard errors are clustered on the PSU level and are reported in parentheses. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 level, respectively. Definitions and sources of the variables are provided in [Table All](#) in the Appendix.

Sample	(1)	(2)	(3)	(4)	(5)	(6)
	PSUs close to RBs in 2006 and not close to ProCredit in 2006					
Households	All households			Low-income households	Middle-income households	High-income households
Dependent variable	Account	Account	Account	Account	Account	Account
LITS 2010	0.177*** [0.060]	0.212*** [0.059]	0.176*** [0.063]	0.153** [0.068]	0.191** [0.091]	0.273*** [0.082]
ProCredit close in 2010	0.067 [0.050]	0.071 [0.047]	0.043 [0.051]	0.016 [0.052]	0.025 [0.058]	0.117 [0.088]
LITS 2010 * ProCredit close in 2010	0.089 [0.075]	0.060 [0.076]	0.119 [0.074]	0.165** [0.073]	0.121 [0.092]	0.000 [0.119]
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
PSU controls	No	No	Yes	Yes	Yes	Yes
Region FE	No	Yes	No	No	No	No
Country FE	Yes	No	Yes	Yes	Yes	Yes
Observations	2,189	2,189	2,189	788	787	614
Number of PSUs	110	110	110	110	110	107
Mean of dependent variable	0.45	0.45	0.45	0.34	0.48	0.57
R ²	0.302	0.320	0.328	0.340	0.325	0.304
Method	OLS	OLS	OLS	OLS	OLS	OLS

substantiate that commercial MFBs such as ProCredit Bank play an important role in deepening access to financial services even in regions in which ordinary RBs already operate large branch networks.

7.2 Expanding the Distance Threshold

In [Table IX](#) we examine how our main results displayed in [Table IV](#) are affected by extending the distance threshold employed in the empirical analysis. We define “closeness” to a ProCredit branch or a RB branch as households lying within a 10-km (instead of 5-km) radius of the nearest branch. Employing this wider radius increases our

sample of PSUs where a RB is close in 2006 but ProCredit is not to 110. Between 2006 and 2010 ProCredit opens a branch within a 10-km radius in 58 of these 110 PSU. Replicating our analysis in Table IV we estimate the difference-in-difference effect of a new ProCredit branch on the use of bank accounts among all households in this sample as well as separately for low-income, middle-income, and high-income households. The results presented in Table IX document a weaker volume effect. In our preferred specification the difference-in-difference estimate for ProCredit (LITS 2010 * ProCredit close in 2010) drops from 21 percentage points (see Table IV, Column 3) to (an imprecisely estimated) 12 percentage points. Estimating the difference-in-difference effect of ProCredit by income group we find a significantly positive effect only for the low-income sample (17 percentage points). The estimated effect is weaker (12 percentage points) and imprecisely estimated for middle-income households, while the estimated effect is zero in the sample of high-income households. These findings suggest—again in line with our theory—that the average impact of a MFB on financial inclusion is weaker the further away households are from the bank. But despite this weaker volume effect, even more distant MFBs exert a disproportionately positive impact on the financial inclusion of low-income households.

8. Conclusions

In this paper we examine how the opening of a branch of a MFB affects the use of bank accounts by households in the vicinity of that branch. We combine household survey data on the use of bank accounts in South-East Europe with the exact geographic location of these households and the branches of the region's major commercial MFB and the largest RBs. We account for local economic activity and population density by using geocoded imagery data on nightlight intensity. This setting allows us to study the additional effect of a commercial MFB on financial inclusion controlling for the presence of RBs and the economic development at a very local level.

Our results suggest that commercial MFBs contribute significantly to financial inclusion. First, we show that ProCredit is more likely to open new branches in regions with a high share of low-income households. Second, we show that the share of households with a bank account increases significantly more in locations in which ProCredit opened a new branch compared with locations where it did not. Third, subsample analyses point to a particularly strong effect of new ProCredit branches on the use of bank accounts by low-income households, older households, and households that rely on transfer income.

Overall, our findings document a significant impact of ProCredit on financial inclusion among households located close to new branches—at least in the first years after a branch has been opened. Due to the limited observation period we cannot, however, establish whether ProCredit has a significant long-term impact on financial inclusion. One challenge for future research, using follow-up waves of the LITS survey, is to examine whether the effects documented by our analysis hold in the long term. That said we believe that our findings have important implications for policy makers who aim to foster financial inclusion. In particular, they suggest that public support of commercial MFBs may help policy makers achieve objectives for financial inclusion even in emerging markets that are served by large retail branch networks of international banking groups.

Appendix

Table A1. Banks per country

This table provides information on the branch networks of the banks considered in the empirical analysis. The first column indicates each bank's rank per country according to the size of the branch network (year-end 2012). The column Branches in 2006 indicates the number of bank branches in 2006. The column Branches in 2010 indicates the number of branches in 2010. The column Type indicates the bank type (Retail bank, Placebo bank, or Commercial MFI). The last column indicates the bank ownership. The information on the bank branch network was obtained from the websites of the banks, central banks, and from the EBRD. The classification of bank ownership is based on [Claessens and Van Horen \(2014\)](#).

Ranking (2012)	Bank	Branches in 2006 (EBRD data)	Branches in 2010 (EBRD data)	Type	Ownership
Panel A. Albania					
1	Raiffeisen Bank Albania	78	102	Retail bank	Foreign
3	Tirana Bank SA—Banka e Tiranës ShA	33	49	Retail bank	Foreign
4	Credins Bank Sh.A	5	32	Retail bank	Domestic-private
6	Banka Popullore Sh.A (Societe Generale)	22	40	Retail bank	Foreign
7	ProCredit Bank (Albania) Sh.A	16	42	Commercial MFI	Foreign
8	Intesa Sanpaolo Bank Albania	23	30	Retail bank	Foreign
10	National Bank of Greece	6	30	Placebo bank	Foreign
Panel B. Bulgaria					
1	UniCredit Bulbank AD	98	250	Retail bank	Foreign
2	United Bulgarian Bank—UBB	112	201	Retail bank	Foreign
4	Raiffeisenbank (Bulgaria) EAD	59	197	Retail bank	Foreign
5	Societe Generale Expressbank	83	126	Retail bank	Foreign
6	NLB Banka Sofia AD	45	134	Retail bank	Foreign
12	Piraeus Bank Bulgaria AD	35	79	Placebo bank	Foreign
14	ProCredit Bank (Bulgaria) AD	42	87	Commercial MFI	Foreign

(continued)

Table A1. (continued)

Ranking (2012)	Bank	Branches in 2006 (EBRD data)	Branches in 2010 (EBRD data)	Type	Ownership
Panel C. Macedonia					
1	Stopanska Banka AD Skopje	48	66	Retail bank	Foreign
2	Komercijalna Banka AD Skopje	48	58	Retail bank	Domestic-private
3	NLB Tutunska banka AD Skopje	22	48	Retail bank	Foreign
4	Procredit Bank AD Skopje	16	42	Commercial MFI	Foreign
7	Ohridska Banka AD Ohrid/Societe Generale	11	25	Placebo bank	Foreign
Panel D. Serbia					
1	Komercijalna Banka A.D. Beograd	160	268	Retail bank	Domestic-state
2	Banca Intesa ad Beograd	132	212	Retail bank	Foreign
5	Eurobank EFG Sredionica AD Beograd	80	107	Retail bank	Foreign
7	Metals Banka Ad Novi Sad	97	122	Retail bank	Domestic-state
8	Raiffeisenbank a.d.	34	82	Retail bank	Foreign
10	UniCredit Bank Serbia JSC	35	69	Placebo bank	Foreign
13	ProCredit Bank Serbia	35	83	Commercial MFI	Foreign

Table AII. Variable definitions and sources

This table presents definitions, sources, and the year of observation for all variables used in the empirical analysis.

Variable name	Definition	Source	Observation
Household characteristics			
Account	Dummy = 1 if any household member has a bank account.	LITS	2006; 2010
Card	Dummy = 1 if any household member has a debit or credit card.	LITS	2006; 2010
LITS 2010	Dummy = 1 if the household was surveyed in the LITS 2010 wave.	LITS	2006; 2010
Income	Household expenses in USD per year (equivalized OECD scale) (natural logarithm).	LITS	2006; 2010
Low income	Dummy = 1 if household expenses are within the lowest/first income tercile per country and wave.	LITS	2006; 2010
Middle income	Dummy = 1 if household expenses are within the middle/second income tercile per country and wave.	LITS	2006; 2010
High income	Dummy = 1 if household expenses are within the highest/third income tercile per country and wave.	LITS	2006; 2010
Wage income	Dummy = 1 if the most important income source is wages in cash or in kind.	LITS	2006; 2010
Self-employed	Dummy = 1 if the most important income source is self-employment, own, or family business or sales or bartering of farm products.	LITS	2006; 2010
Transfer income	Dummy = 1 if the most important income source is transfer income from the state (e.g., pensions)	LITS	2006; 2010
Some wage income	Dummy = 1 if some income is from wages in cash or in kind.	LITS	2006; 2010
Some self-employment	Dummy = 1 if some income is from self-employment, own or family business or sales or bartering of farm products.	LITS	2006; 2010
University degree	Dummy = 1 if the respondent has a university degree.	LITS	2006; 2010
Household size	Number of household members (adults and children).	LITS	2006; 2010
Age	Age of the household head (natural logarithm).	LITS	2006; 2010
Female	Dummy = 1 if the household head is female.	LITS	2006; 2010

(continued)

Table AII. (continued)

Variable name	Definition	Source	Observation
Language	Dummy = 1 if the respondent speaks an official national language.	LITS	2006; 2010
Muslim	Dummy = 1 if the respondent is muslim.	LITS	2006; 2010
Car	Dummy = 1 if the respondent or anyone in the household has a car.	LITS	2006; 2010
Computer	Dummy = 1 if the respondent or anyone in the household has a computer.	LITS	2006; 2010
Mobile phone	Dummy = 1 if the respondent or anyone in the household has a mobile phone.	LITS	2006; 2010
Internet	Dummy = 1 if the respondent or anyone in the household has internet access.	LITS	2006; 2010
PSU characteristics			
ProCredit close in 2006	Dummy = 1 if a ProCredit branch is within 5 km travel distance to the PSU in 2006.	GoGLEmaps; Bank websites	2006
Retail banks close in 2006	Dummy = 1 if a Retail bank branch is within 5 km travel distance to the PSU in 2006.	GoGLEmaps; EBRD	2006
Placebo bank close in 2006	Dummy = 1 if a Placebo bank branch is within 5 km travel distance to the PSU in 2006.	GoGLEmaps; EBRD	2006
ProCredit close in 2010	Dummy = 1 if a ProCredit branch is within 5 km travel distance to the PSU in 2010.	GoGLEmaps; Bank websites	2010
Retail banks close in 2010	Dummy = 1 if a Retail bank branch is within 5 km travel distance to the PSU in 2010.	GoGLEmaps; EBRD	2010
Placebo bank close in 2010	Dummy = 1 if a Placebo bank branch is within 5 km travel distance to the PSU in 2010.	GoGLEmaps; EBRD	2010
Nightlight 2006	Nightlight in 2006 per PSU (intercalibrated). Data values range from 0 to 63.	US National Oceanic and Atmospheric Administration Earth Observation Group	2006; 2010
D.Nightlight (2010–2006)	Change in Nightlight per PSU (2010–2006).		2006; 2010
Nightlight 2006 (orthogonalized)	Nightlight in 2006 per PSU (intercalibrated) orthogonalized by population in 2006.		2006; 2010
Population 2006 (Ln)	Population in 2006 (in thousands) per PSU (natural logarithm).	LandScan	2006; 2010
D.Population (2010–2006)	Dummy = 1 if the population of the PSU increased between 2010 and 2006 (relative ranking of the PSU by population per country).	LandScan	2006; 2010

(continued)

Table AII. (continued)

Variable name	Definition	Source	Observation
Number of Retail banks in 2006	Number of Retail bank branches in 2006 that are within 5 km travel distance to the household.	Googlemaps; EBRD	2006; 2010
D.Number of Retail banks (2010–2006)	Change of the number of Retail bank branches that are within 5 km travel distance to the household between 2006 and 2010.	Googlemaps; EBRD	2006; 2010
Share of low-income households	Share of households that have income in the lowest income tercile by country and year (per PSU).	LITS	2006; 2010
Share of middle-income households	Share of households that have income in the middle income tercile by country and year (per PSU).	LITS	2006; 2010
Share of high-income households	Share of households that have income in the highest income tercile by country and year (per PSU).	LITS	2006; 2010
Average income per PSU	Average household expenses per PSU (natural logarithm).	LITS	2006; 2010
Share wage income per PSU	Share of households that report wage income to be their primary income source (per PSU).	LITS	2006; 2010
Share self-employed per PSU	Share of households that report self-employment to be their primary income source (per PSU).	LITS	2006; 2010
Rural	Dummy = 1 if the PSU is located in a rural area (as defined by the EBRD LITS survey).	LITS	2006; 2010

Table AIII. Summary statistics

This table reports summary statistics of all variables in the years 2006 and 2010. Note that the *exponentiated* values of ln-transformed variables (age, income, average income per PSU, population 2006) are shown in this table. Definitions and sources of the variables are provided in Table AII.

Variable	LITS 2006				LITS 2010			
	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
Household characteristics								
Account	0.28	0.45	0	1	0.53	0.50	0	1
Card	0.29	0.45	0	1	0.46	0.50	0	1
Income	2,320	1,610	3	28,337	3,609	2,176	63	22,789
Low income	0.33	0.47	0	1	0.33	0.47	0	1
Middle income	0.33	0.47	0	1	0.34	0.47	0	1
High income	0.33	0.47	0	1	0.33	0.47	0	1
Wage income	0.44	0.50	0	1	0.45	0.50	0	1
Self-employed	0.18	0.38	0	1	0.20	0.40	0	1
Transfer income	0.38	0.49	0	1	0.35	0.48	0	1
Some wage income	0.56	0.50	0	1	0.56	0.50	0	1
Some self-employment	0.29	0.45	0	1	0.31	0.46	0	1
University degree	0.16	0.36	0	1	0.16	0.37	0	1
Household size	3.44	1.74	1	12	3.18	1.65	1	12
Age	53.30	14.58	18	98	54.34	14.55	18	95
Female	0.21	0.41	0	1	0.24	0.43	0	1
Language	0.99	0.10	0	1	0.94	0.24	0	1
Muslim	0.26	0.44	0	1	0.27	0.44	0	1
Car	0.44	0.50	0	1	0.52	0.50	0	1
Computer	0.25	0.43	0	1	0.52	0.50	0	1
Mobile phone	0.74	0.44	0	1	0.85	0.36	0	1
Internet	0.14	0.34	0	1	0.41	0.49	0	1
Observations				3,992				4,244

(continued)

Table AIII. (continued)

Variable	LITS 2006				LITS 2010			
	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum
PSU characteristics								
ProCredit close in 2006	0.38	0.49	0	1	0.41	0.49	0	1
Retail banks close in 2006	0.61	0.49	0	1	0.65	0.48	0	1
Placebo bank close in 2006	0.31	0.46	0	1	0.35	0.48	0	1
ProCredit close in 2010	0.50	0.50	0	1	0.57	0.50	0	1
Retail banks close in 2010	0.66	0.48	0	1	0.68	0.47	0	1
Placebo bank close in 2010	0.48	0.50	0	1	0.51	0.50	0	1
Nightlight 2006	22.03	17.66	0.07	62.88	23.28	18.32	0.00	62.97
D.Nightlight (2010–2006)	0.96	2.79	−4.84	12.56	1.32	2.77	−3.65	11.69
Nightlight 2006 (orthogonalized)	−0.64	8.56	−20.60	25.65	0.60	9.03	−20.60	36.12
Population 2006	64.19	95.37	0.12	367.19	72.05	105.11	0.04	369.14
D.Population (2010–2006)	0.67	0.47	0.00	1.00	0.62	0.49	0.00	1.00
Number of Retail banks in 2006	6.32	11.54	0.00	60.00	7.17	11.45	0.00	49.00
D.Number of Retail banks (2010–2006)	3.10	5.36	0.00	25.00	3.52	5.48	0.00	25.00
Share of low-income households	0.33	0.22	0.00	1.00	0.33	0.22	0.00	1.00
Share of middle-income households	0.33	0.13	0.00	0.70	0.34	0.13	0.00	1.00
Share of high-income households	0.33	0.21	0.00	1.00	0.33	0.22	0.00	1.00
Average income per PSU	2,007	757	430	5,709	3,217	1,067	237	7,392
Share wage income per PSU	0.44	0.21	0.00	0.95	0.45	0.19	0.00	1.00
Share self-employed per PSU	0.18	0.17	0.00	1.00	0.20	0.19	0.00	0.86
Rural	0.40	0.49	0.00	1.00	0.39	0.49	0.00	1.00
Observations				3,992				4,244
PSUs				200				221

Supplementary Material

Supplementary material are available at *Review of Finance* online.

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