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Allison Benson and Jean-Paul Faguet

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Department of International Development

London School of Economics and Political Science

Houghton Street

London

WC2A 2AE UK

Tel: +44 (020) 7955 7425/6252

Fax: +44 (020) 7955-6844

Email: j.p.faguet@lse.ac.uk

Website: www.lse.ac.uk/InternationalDevelopment

Increasing Access to Formal Agricultural Credit: The Role of Collective Action Organizations

Allison Benson[1] Jean-Paul Faguet[2]

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Abstract

Collective action (CA) allows individuals to overcome market and state failures, something particularly relevant in rural areas and highly imperfect markets such as agricultural credit. To analyse the relation between CA in the form of Rural Producer Organizations (RPOs) and access to agricultural credit, we estimate a logit model exploiting data on 2.3 million farmers in Colombia, as well as a fixed effects model using original data on 15,000 municipality-year observations of RPOs and credit allocation. We find a positive relationship between CA and access to credit at both the farmer and municipality levels. The relationship is heterogeneous, varying by farmer size and credit source. For credit allocated to small farmers, we find a positive relation, but only via public credit; for credit allocated to large farmers, the relation is also positive, but only via private credit. We find no effect of CA on medium-size farmers' access to credit. Our results imply that CA's potential to foster rural financial development depends on pre-existing contextual conditions, notably the segmentation of the credit market. The distributional effects of CA, and its dependence on contextual conditions, should be considered carefully in policy design.

Key words: Agricultural credit, credit constraints, collective action, rural producer organisations, Colombia.

[1] Department of International Development, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK.

[2] Department of International Development and STICERD, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK.

1. Introduction

Access to agricultural credit is important for rural development as it can help increase productivity, output, and income, as well as reduce poverty (Bukari et al., 2021; Ali, Deininger & Duponchel 2014, Conning & Udry 2007, Burgess & Pande 2005; Echavarria et al. 2017; Regasa et al., 2021). Despite this, over 1.7 billion people around the world continue to have limited or no access to formal credit (Demirgüç-Kunt et al., 2018; Banerjee & Duflo; 2006; Giné, 2011).

Can collective action help increase access to agricultural credit? Following Olson (1965), Ostrom (1990), and many others, we define collective action (CA) as individuals working together in pursuit of a common objective. We address this question by focusing on a particularly important and widespread form of CA in rural areas: Rural Producer Organizations (RPOs). These include agricultural cooperatives, rural associations, and other organizations in which farmers voluntarily invest time, effort and resources to improve their production and commercialization opportunities. CA both enables and is strengthened through RPOs, allowing farmers to profit from vertical and horizontal integration, which has been shown to ease access to input and output markets (Verhofstadt & Maertens 2014, Conley & Udry 2003, Bebbington 1997, Narrod et al. 2009). We extend this line of research by investigating whether CA can also ease access to rural financial markets.

We start by analysing data on over 2.3 million Colombian farmers' participation in CA organizations and access to agricultural credit. We estimate a logit model, and find that RPO membership makes farmers 2.5 times more likely to receive agricultural credit. This is in line with previous studies documenting the relevance of social relations in fostering financial inclusion (Dufhues et al. 2013; Okten & Osili 2004; Markussen & Tarp 2014).

From a development perspective, it is relevant to analyse whether the potential of CA in fostering financial inclusion generates distributional effects – that is, whether it benefits some type of farmers more than others. For instance, if RPO membership increases access to credit for members, it could do so by crowding-out resources available for non-members, leaving aggregate (local-level) access to credit constant and making the development impact of access to credit uncertain. To explore this, we analyse the aggregate relation between CA and access to credit, focusing on municipal-level data. To this end, we build a novel panel dataset identifying existing RPOs in each of the 1,100 Colombian municipalities during a 15-year period. We estimate a fixed effects (FE) model of aggregate credit uptake, controlling for historical, institutional and cultural factors that typically confound inferences made on small samples, as well as cross-country and cross-section data (Faguet, 2012). The FE model controls for various sociodemographic time-varying characteristics, as well as for municipality, year and department-year fixed effects. Despite including these controls, we cannot rule out the existence of endogeneity caused by municipality and time-varying unobserved variables that can affect access to credit, or that can confound both access to credit and RPO formation. We are not able to exploit exogenous sources of variation to conduct this analysis; nonetheless, as part of our robustness tests, we run a model comparing municipalities in which treatment commences at different points in time (where 'treatment' is an increase in the number of RPOs) with similar municipalities where treatment could have started but has not yet done so. Our main results prove robust. In any case, these results should be interpreted as relations rather than as causal effects, as the estimation strategies cannot fully account for the aforementioned sources of possible endogeneity.

Our aggregate-level results indicate a positive relation between increases in the levels of CA in a municipality and increases in access to credit at both the extensive (total *number* of agricultural credits in a municipality) and intensive (total *value* of credits allocated) margins. This suggests that there is no crowding-out of credit between members and non-members of CA organizations, implying that CA has the potential to foster local financial development in contexts where credit supply is not fixed. This finding contributes to the literature analysing potential solutions for increasing access to rural credit (Ali et al. 2014; Guirkinger & Boucher, 2008; Boucher & Guirkinger, 2007; Carter & Olinto, 2003; Conning & Udry, 2005).

Banerjee et al. (2015) note that the literature on rural credit has given limited attention to distributional effects.[3] We attempt to shed light on this by analysing whether the relation between CA and credit is heterogeneous for different types of farmers. We focus on differences in credit allocated to small, medium or large farmers (using standard Colombian classifications based on the value of farmer assets[4]), and on differences in the source of credit – public vs. private (commercial) banks. For small farmers, we find a positive relation between CA and credit, but only via increased access to public credit. For large farmers the relation is also positive, but this time via increased access to private credit. We find no relation for credit allocated to medium-scale farmers.

This heterogeneity is likely explained by binding pre-existing contextual conditions, in this case, the structural segmentation of the rural credit market. Private banks bias lending towards large farmers in order to lower fixed approval costs and risk levels, while public banks following normative development objectives favour small farmers. Medium-sized farmers are left rationed out. CA appears to be replicating, rather than counteracting, this sorting of credit. These results highlight the heterogeneous potential of CA as a development tool, as well as its dependence on contextual conditions, contributing to the literature on collective action (Ostrom, 1990; Uphoff, N. & Wijayaratna, 2000) and on rural collective action organizations (Desai & Joshi, 2014; Vandeplas et al. 2013; Abebaw & Hail, 2013; Markussen & Tarp, 2014; Bebbington, 1997).

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[3] Some studies have analysed differences between formal and informal sources of credit (Giné 2011, Boucher and Guirkinger 2007 & 2008), but few focus on heterogeneous effects within formal sources (i.e. public and private credit) or on heterogeneity in recipient type.

[4] According to Finagro (the Agricultural Sector Finance Fund), small farmers have capital worth less than $93 million COP (US$ 34,370), and medium size farmers have capital worth less than $3,467 million COP (US$ 1.28 million).

The remainder of this paper is structured as follows: section 2 analyses rural credit markets theoretically in terms of information and incentives, focusing on the role of RPOs. Section 3 discusses our empirical setting. Section 4 provides details on our data, and section 5 on the empirical strategy. Results are presented in section 6, and robustness tests in section 7. Section 8 discusses the results, and section 9 concludes.

2. Information, Incentives, Rural Credit and RPOs

Despite the relevance of agricultural credit for rural development, millions of farmers continue to face credit constraints that limit their ability to carry out productive investments (Boucher et al. 2009). While microfinance has introduced new credit opportunities, it does not provide the full range of products demanded by rural households. For instance, a survey conducted in Colombia shows that 92% of farmers prefer to finance their investment through credit from banks or cooperatives (Econometría & M. Consultores, 2014). This is because formal credit offers better conditions, including lower interest rates, longer terms and larger credit amounts (Giné, 2011; Guirkinger & Boucher, 2008).

The inexistence or incompleteness of agricultural credit markets derive from information and enforcement problems that lead to moral hazard and adverse selection (Conning & Udry, 2009; Boucher et al. 2009). Information is costly to access in rural areas, where population and production units are dispersed and physical and technological infrastructure is precarious. Even access to information (e.g. on producers' experience) does not provide financial institutions with certainty, as output and revenues are vulnerable to weather conditions and fluctuations in international commodity prices and exchange rates. On the demand side, most farmers lack the time to travel long distances to banks, and the human capital required for carrying out complex credit applications. State failures also affect rural financial markets, for instance when weak property rights make land unsuitable for collateralization (Conning & Udry 2005; ILO, 2015).

Another characteristic of rural credit markets is high fragmentation. Different types of farmers (small, medium, and large) are sorted across different sources of credit. Private banks tend to favour larger farmers, as fixed approval and disbursement costs constitute a smaller proportion of costs in larger credits. Large producers are also perceived as more creditworthy, as they tend to have more fixed capital that can be used as collateral, reducing credit risk and contributing to banks´ financial stability (United Nations 2006). Incentive schemes for credit analysts in private banks based on the total value of credit allocations can also generate a bias towards large transactions. Meanwhile, public banks tend to favour small farmers, following normative considerations (i.e. their mission to promote rural development) as well as regulations that favour small farmers (e.g. a cap on the size of credits they can lend). This sorting of credit has important development implications, as different sources of credit offer different conditions and benefits (e.g. interest rates, guarantee requirements, payment schemes). Hence, whether CA can lessen credit constraints and reduce the sorting of credit are important questions to analyse.

The literature on rural credit has addressed the relation between social relations and access to credit mainly by studying microcredit and informal forms of CA. For example, Karlan (2007) shows that individuals with stronger social connections to other microfinance group members have higher repayment rates and higher savings. There is also evidence that trust and trustworthiness arising from social relations increase group loan repayment (Cassar, Crowley & Wydick, 2007; Karlan, 2005). Fewer studies have analysed the impact of social relations on formal agricultural credit. A few show that social networks reduce credit constraints (Dufhues et al., 2013; Heikkilä et al. 2009; Guirkinger & Boucher, 2008). There is also evidence that participation in village committees and social organizations can increase the likelihood of individuals accessing credit (Okten and Osili, 2004; Markussen & Tarp, 2014). Reyes &

Lensink (2011) show that being part of a production cluster also improves access to credit for market-oriented large producers.

There are various mechanisms through which CA in the form of RPOs could ease access to agricultural credit. First, RPO membership can reduce quantity credit constraints:[5] it can increase the supply of credit as RPO membership signals both farmer and productive project quality, making banks more willing to lend to organised farmers. Benson (2019) documents how banks treat RPOs as important signalling devices; from a bank's perspective, farmers who market their products through RPOs are likely to have better commercial opportunities and bear less risk. RPOs also provide financial information to banks, including informal financial histories on in-house input credit and group lending schemes. These signals screen clients and lessen problems of imperfect and asymmetric information that typically reduce the supply of credit.

RPOs can also reduce transaction-cost credit constraints. For instance, banks offer and approve several individual credits in a block when they visit RPOs, being able to find, offer and process various credits at once. Reducing search and allocation costs is crucial for reducing the biases banks have towards small operations.

Furthermore, Benson (2019) shows that when farmers join RPOs, their demand for credit increases as they are able to engage in more profitable and larger projects through the organization. For example, RPOs typically improve members' access to inputs, technology, output markets, and government support (often targeted to farmer organizations). Also, once farmers join RPOs, they become eligible to apply to associative credit – credit directed towards organizations, rather than individuals, typically offering subsidised interest rates and other benefits. From the demand side, CA can also reduce transaction-cost credit constraints that lead to self-rationing. Information, including information on credit opportunities and on the credit

[5] We follow the classification of credit constraints proposed by Guirkinger & Boucher (2008).

application process, flows more rapidly and cheaply through RPOs.

Finally, RPOs can reduce risk-related credit constraints that typically restrain demand. For example, RPOs can act as a safety net, providing informal lending (from the organization or one of its members) that help farmers meet formal credit repayments in cases of low liquidity, which reduces farmers' fear of losing their collateral. Bouquet et al. (2015) show that family networks can act as gateways to formal financial inclusion. RPOs appear to play the same role.

It is important to note that the potential mechanisms through which RPOs increase access to credit are not limited to RPO members. The benefits of CA can spill over onto non-members and the community in general. Benson (2019) shows that there is informal sharing of information between RPO members and non-members, including on credit opportunities and application processes. Some RPOs provide services directly to non-members (e.g. allowing non-members to market their crops though them). More generally, RPOs generate jobs, contribute to the provision of public goods such as roads, and – very importantly – attract financial resources from public programs and private investors. All of this increases the flow of money and makes the local economy more dynamic, plausibly increasing both the demand and supply of credit. Hence CA can lead to increases in credit not only for RPO members, but also at the aggregate local level.

3. Setting

3.1 The Agricultural Credit Market in Colombia

As in most developing countries, a large share of farmers in Colombia are credit constrained. According to the agrarian census of 2013, only 11% of rural producers access credit in any given year. A large share (around 65%) of agricultural credit – credit used for production in agriculture – is provided by the public bank (Banco Agrario), targeting mainly small farmers[6] with credits averaging COP $8 million (US $2,956). Credit from private banks accounts for 20% of credits, targeted mainly to large farmers with credits averaging COP $526 million.[7] Both public and private credit are subject to governmental regulation on interest rates and guarantee schemes[8]. Financial and credit cooperatives[9] also allocate credit, although credit cooperatives are not present in all municipalities, and the number of agricultural credits they allocate remains small. Table A1 in the annex provides a detailed description of the differences in credit conditions and benefits across credit sources.

Throughout the study period, credit allocated to small farmers represented 84% of all credits (and 23% of total resources), consistent with the fact that 89% of the 2.3 million farmers in Colombia are small. Credit to medium-scale farmers represented 14% of all credits (34% of resources), while credit for large farmers represented 2% of credits (43% of resources). Finally, note that agricultural credit is allocated throughout the whole country, with no credit targeting strategies to particular regions, products or farmer types.

3.2 Collective Action in Rural Colombia

Little is known about RPOs in Colombia. Most analyses rely on case studies or on the diagnosis of a small number of organizations. As far as we are aware, this is the first study to systematically identify existing RPOs by number and type across all municipalities in the country, as we further describe in the data section. We find that between 2002 and 2015, over

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6 As mentioned in the introduction, categories of farmer size are defined by the public agency, Finagro, according to the value of farmers' assets.

7 Commercial banks in Colombia are forced by law to invest a fixed share of their checking and savings accounts in TDAs (Agricultural Development Titles). These resources are managed by Finagro, a second level bank, and are transferred to the public banks to finance its own credit allocations. Commercial banks have the alternative of granting agricultural credits directly, which substitute for the forced investment requirements. Public loan guarantees are an important policy tool, covering 88% of credits and acting as an incentive for increasing credit supply and demand.

8 Interest rate ceilings favour small farmers (interest rates: 12% vs. 13% for medium and 14.6% for large). This aims to counteract the natural tendency of the market to charge higher interest rates for small loans (Banerjee and Duflo 2010). The market interest rate for small credits is lower in the public bank than in commercial banks, while for larger credits, private banks can offer more competitive interest rates.

9 These operate as banks, not as agricultural cooperatives (focusing on productive and commercialization services)

27,000 RPOs were created and formally registered.[10] We are also able to show that there are RPOs throughout the country, with some concentrations in central and south-western regions (see annex maps A1 and A2). We further document that exit rates are much lower than entry rates (the average number of RPOs cancelled per year is equivalent to 5% of RPOs created[11]) and that most RPOs focus on the production of a particular product (most commonly cattle ranching, coffee, cocoa, fruit, and milk[12]).

Fieldwork analysis (Benson 2019) shows that these organizations operate at a very local level, and that members tend to be homogeneous in terms of how much land they own, how much they produce, and how they produce. Regarding organization size, the average number of members is around 25, although some have over 100. The author also documents the high heterogeneity in the functioning and success of RPOs, which relates to whether they are created organically (as bottom-up initiatives with long-term production objectives) or inorganically (following an external, short-term stimulus, such as the government requiring being organized in order to access specific benefits). Successful organizations provide a variety of services to their members, including joint commercialization and application to public programs offering technical and financial support.

According to the agrarian census, 10% of rural producers in Colombia are members of RPOs[13] and participation rates across farmer sizes are similar: 10% for small, 11% for medium,

[10] RPOs register with the Chambers of Commerce. The registry process is not costly, but requires members to fill out forms and establish their own statutes, among others.

[11] There can be underreporting of cancellations. However, RPOs are legally required (by Decree 019 of 2012) to update their registry annually, and thus we have information on the last update date, allowing us to identify whether RPOs are active.

[12] Based on individual level data from the Census, we find that 69% of members engage in agricultural commercial activity, 19% in livestock production, while fishery and forestry account for less than 3%. There are no significant differences in the rate of RPO participation according to activity.

[13] Low participation rates can result from a lack of information about their benefits, or participation costs, which can be higher than the expected return. There are also non-trivial coordination and transaction costs, including negotiating divergent interests among members, making collective decisions, monitoring compliance with rules and solving conflict (Vitaliano, 1983; Ostrom, 1990). These costs imply that collective action is not a universal or cost-free alternative for enhancing rural development.

and 12% for large.[14] We carry out a logit analysis of the predictors of RPO participation; the main ones are farmers' engagement in commercial activity (e.g. selling produce in a market), receiving technical assistance, and owning agricultural machinery.

Turning now to our main subject, the relation between CA and access to credit, Figure 1 provides suggestive evidence on how municipalities with higher levels of CA have better access to credit. We categorise municipalities as high vs. low CA based on their number of RPOs per capita compared to the national average. It is important to note that the steep increase in number and value of credits allocated in the country is largely explained by changes in measurement. Over time, regulators have broadened the legal definition of agricultural credit to include various rural activities, and even credits to supermarkets and restaurants, so inflating the credit count.[15] This phenomenon does not undermine our identification (see below), as our concern is to analyse the distribution of credit across farmers and municipalities, not overall levels of reported credits.

[14] Note that these size categories are not comparable to the small, medium and large farmers' credit categories, which are defined based on capital, not plot size.

[15] It also relates to reductions in regulatory aspects (re-discounting margins), that generate incentives for banks to report as agricultural credit, large credits not necessarily corresponding to agricultural activity in the pure sense.

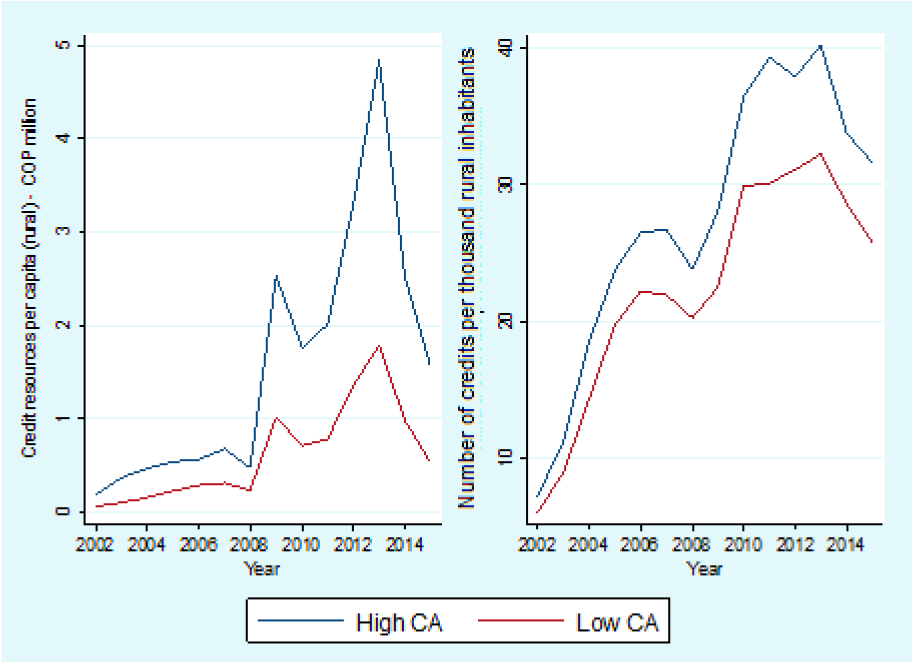

Figure 1. Real value (panel A) and number (panel B) of agricultural credits granted per municipality – municipalities with high vs. low levels of CA
Source: Author's calculations based on data from Finagro and the National Economic and Social Registry RUES.

4. Data

For the individual-level analysis, we rely on the national agrarian census of 2013, reporting data on over 2.3 million rural producers.[16] Data includes self-reported RPO membership, access to credit, farmer age, plot size, education level, access to health, ethnic background, ownership of agricultural machinery, and access to technical assistance. For the municipal-level analysis, we rely on secondary data on credit allocations reported by Finagro (the Agricultural Sector Finance Fund). This includes the total number and total value of agricultural credits granted per municipality per year between 2002-2015. We disaggregate this data to show credit allocated to small, medium and large farmers, employing the standard

[16] Census data refers to agricultural productive units – UPA, defined as the unit of organization for production managed under one producer. 96% of UPA are composed by one household and managed by one producer. Thus, for simplicity, we use the term producer or farmer instead of UPA.

Finagro classification of farmer size based on the value of farmer assets. We also classify credit data based on whether it is granted by the public bank or by private banks.[17]

Our data on RPOs per municipality-year is original. We built it based on microdata from the Unique Economic and Social Registry (RUES) managed by the confederation of commerce chambers.[18] In order to identify RPOs from the universe of 260,000 registered social organizations, we designed an algorithm that searches names containing a set of 250 words that can identify RPOs (e.g. farmer, rural producer, coffee, tomatoes, banana) and, when data quality allowed it, merged the results with data points reporting organization type (e.g. association, cooperative) and economic activity (e.g. agriculture, manufacturing). We then manually validated each potential RPO register, and built a dataset of over 27,000 RPOs. This is the first RPO panel database built in the country. It is part of the contribution of this paper, and we have made it publicly available.[19]

Data on local economic and social conditions was obtained from the University of the Andes' Centre for Research in Economic Development (CEDE). Information on homicide rates comes from the Ministry of Defence. Data on intragovernmental transfers and local tax revenues comes from National Planning Department (DNP). We also used weather data from the Institute of Environmental, Hydrological and Meteorological Studies (IDEAM) to build a weather shock variable. This variable relies on municipality-month data on centimetres of rain. Each municipality-month data point is compared to its historic average, and observations beyond one standard deviation above or below that average, are marked as a rain shock. The sum of rain shocks per year comprises our yearly weather shock measure.

[17] We cannot classify credit based on whether it was allocated by credit cooperatives, as only a minority of these grant credit through Finagro. Information on credit granted by suppliers, money lenders or other sources is also unavailable.

[18] Social organizations are required to register and update their register annually. RPOs have incentives to do this, despite it having a cost, as public programs and banks require organizations to be registered. Nonetheless, not all RPOs carry out this registry or update, and thus RPO creation is probably underreported.

[19] Dataset available in https://reshare.ukdataservice.ac.uk/ labelled as *Data on collective action organizations and agricultural credit in Colombian municipalities (2021).*

Summary statistics are presented in Table A2 in the Annex. The mean number of RPOs per thousand rural inhabitants is 0.2, and the mean number of agricultural credits per thousand rural inhabitants is 22.6. The mean number of credits allocated to small farmers is 18.2, to medium-size farmers is 2.2, and to large farmers is 0.14.

5. Empirical Strategy

We first carry out an analysis of the relationship between CA and access to credit at the individual level. Relying on census data we estimate a logit model in which the dependent variable is a dummy indicating whether the farmer *requested* credit during the past year (equation 1). We estimate a second model in which the dependent variable is a dummy indicating whether the farmer *received* the requested credit (equation 2). In both equations, the key independent variable is dummy *CA,* indicating whether the farmer is a member of an RPO. Socioeconomic controls in vector X include age, gender, level of education, access to machinery, access to technical assistance, and participation in other social organizations.

$$P\ (requested\ credit)_i = \beta_0 + \beta_1 X_i + \beta_2 CA_i + \ \epsilon_{it} \qquad (1)$$

$$P\ (received\ credit)_i = \beta_0 + \beta_1 X_i + \beta_2 CA_i + \ \epsilon_{it} \qquad (2)$$

Our main analysis is carried out at municipal level. We estimate a fixed effects (FE) model for the universe of Colombian municipalities (1100+) between 2002-2015. We first estimate a model in which dependent variable $NC_{m,t}$ is the *number* of agricultural credits granted per capita[20] in municipality m and year t (equation 3). This measures access to credit at the extensive margin. We then estimate a model in which dependent variable $VC_{m,t}$ is the real $value$ of agricultural credits allocated per capita in a municipality (equation 4). This captures access to credit at the intensive margin.

$$NC_{m,t} = \beta_0 + \beta_1 X_{m,t-1} + \beta_2\ \ CA_{m,t} +\ \mu_m + \delta_t +\ \gamma_{d,t} + \epsilon_{mt} \qquad (3)$$

[20] Per capita refers to rural population for dependent and independent variables.

$$VC_{m,t} = \beta_0 + \beta_1 X_{m,t-1} + \beta_2 \; CA_{m,t} + \; \mu_m + \delta_t + \; \gamma_{d,t} + \epsilon_{mt} \tag{4}$$

The independent variable in both equations is CA, measured as the number of RPOs per thousand rural inhabitants in municipality m and year t. Unfortunately, time-series data on the number of farmers participating in RPOs per municipality is not available. As a robustness check, we run a cross-section analysis for the census year comparing both measures of CA (number of RPOs per capita and share of farmers participating in RPOs).[21]

Equations 3 and 4 include a vector (X) of observable municipal characteristics that vary in time and can affect credit provision as well as RPO creation. These include transfers from central and departmental governments, and so control for public investment that likely affects credit dynamics as well as opportunities for creating and sustaining RPOs (e.g. investment in a new water district or road that will increase agricultural productivity or commercial opportunities). We also control for local tax revenues in order to account for the dynamism of the local economy, controlling, for instance, for price shocks in particular products that can affect municipalities differently; by affecting liquidity in the local economy, such factors can affect both the demand and supply of credit, as well as production and commercialization opportunities driving CA dynamics. We also control for the number of homicides per capita as a measure of insecurity. Insecurity can affect the capability of banks operating in an area, and can also influence their risk analysis. Insecurity also drives farmers' decisions on whether or not to invest[22] and whether or not to join RPOs. We include the aforementioned weather shock variable as an additional control, since changes in weather conditions affect credit demand and supply, given changes in repayment behaviour and risk of default (Adjognon et al. 2020).

[21] There is no consensus on whether larger or smaller RPOs are more "successful", as the benefits of economies of scale in larger organizations trade off against their higher costs of free riding, coordination and enforcement. The literature typically describes a U-shape hypothesis (Naziri et al. 2014).

[22] An ongoing study shows that credit demand is affected by security conditions, in particular by the 2016 FARC guerrilla demobilization (De Roux & Martinez, 2020).

Our specification includes a municipality fixed effect (μ_m) that controls for time invariant municipal characteristics that can drive the demand and supply of agricultural credit, for example distance to the capital city, a proxy for market integration. Other examples include local cultures of entrepreneurialism and debt repayment. This fixed effect also controls for variables that do not vary significantly over the period studied (e.g. land quality, strength of economic institutions).

We include a time fixed effect (δ_t) that controls for aggregate variations affecting all municipalities over a given period, for example macroeconomic and political cycles. Finally, we include a department-year fixed effect ($\gamma_{r,t}$) to control for aggregate variations affecting all municipalities in a department during a given year. Examples include a natural disaster or an upsurge of violence. Finally, standard errors ϵ_{mt} are clustered at municipal level to control for potential serial and spatial correlation.

We deal with endogeneity related to omitted variable bias by controlling for time-varying observables and including municipality, year, and department-year fixed effects. However, these controls do not account for potential endogeneity caused by municipality and time-varying unobserved variables. There could also be endogeneity due to reverse causality: For example, Phan et al. (2020) show that microcredit improves rural households' social network quantity and quality, and Fischer & Qaim (2012) find that access to credit has a positive effect on participation in farmer organizations.

Considering these threats to identification, we explored the possibility of exploiting exogenous sources of variations such as policy interventions or natural shocks. The only possible treatment that took place during the period was a law restructuring the solidarity sector (creation of a new public agency and new requirements for creating and registering social organizations). But this is a national level change affecting all municipalities in equal measure.[23] It did not generate exogenous variation across time and municipality groups that could be analysed in a standard differences-in-differences approach.

As an alternative, we propose an estimation in which we focus on the subsample (50%)[24] of municipalities that had not received any CA treatment (where "treatment" is an increase in the number of RPOs) at the start of our study period. In each municipality, treatment then switches on at time t when the number of RPOs increases. We compare municipalities where the level of CA increased (municipalities 'treated' at different points in time), with similar municipalities where treatment could have started but has not yet done so.[25] We show that municipalities in the employed subsample are similar to the average Colombian municipality (Table A3) and are scattered throughout the country (Map A3), suggesting that there are no systematic underlying variables driving the nature of the sample composition. The reduced-form equation of this model is:

$$NC_{m,t} = \beta_0 + \beta_1 X_{m,t-1} + \beta_2 T_{m,t} + \mu_i + \delta_t + \varphi_{r,t} + \epsilon_{mt} \quad (5)$$

$$VC_{m,t} = \beta_0 + \beta_1 X_{m,t-1} + \beta_2 T_{m,t} + \mu_i + \delta_t + \varphi_{r,t} + \epsilon_{mt} \quad (6)$$

In both equations, β_2 is the coefficient of interest and $T_{m,t}$ is the treatment indicator, which, as mentioned above, varies across municipality and year. As in the FE model, we include observable controls as well as municipal, time, and department-year fixed effects. Note that the municipal fixed effect captures ex-ante differences in CA levels. The underlying assumption for identification in models exploiting double differences between groups and periods is that counterfactual outcomes in the absence of treatment are independent of treatment. In cases in

[23] Sectoral experts we interviewed confirmed this.
[24] The sample is comprised by 532 municipalities. Ideally, we would define the subsample as those municipalities with zero RPOs. However, these (123) municipalities are statistically different to the rest of the municipalities in the country in several socioeconomic dimensions, making them a non-representative subsample. Furthermore, the sample size would reduce the power of the estimations.
[25] By 2015 virtually every municipality was treated, as shown in Annex Figure A1. Although possible contagion effects from treatment to control municipalities cannot be ruled out, the majority of RPOs operate solely at municipal level, suggesting that contagion effects should not be a major threat.

which there are multiple treatment and control groups, this is tested running regressions of treatment leads and lags (Angrist & Pischke 2008). In our model, the test is formalised as:

$$Y_{m,t} = \beta_0 + \beta_1 X_{m,t-1} + \sum_{j=-l}^{q} \beta_j T_{m,t}(t = k + j) + \mu_m + \delta_t + \epsilon_{mt} \quad (7)$$

where k is the time at which the treatment is switched on in municipality m. The identification assumption to be tested is that $\beta_j = 0$ *for all j<0*, that is, that the indicator variables for periods prior to the adoption of treatment are not significant.

6. Results

Table 1 presents results from our first analysis, the logit model. They show that CA, measured as RPO membership, leads to a 2.5-fold increase in the probability of a farmer requesting credit (the probability of credit demand).[26] These results are robust to the inclusion of controls (column 2). Column 3 shows that RPO membership increases the likelihood of a farmer receiving requested credit by 1.2 times. We call this the probability of credit supply conditioned on demand. It is conditional as it is only estimated on the subsample of farmers requesting credit. In column 4 we see that these results are also robust to the inclusion of controls.

Logit results shows that RPO membership is a relevant predictor of access to credit; the magnitude of this effect is larger than other farmer characteristics, including gender, age, ethnicity, education, owning agricultural machinery, participating in other social organizations, or accessing the subsidised health system (a proxy for poverty). Note, however, that because there is self-selection in both joining an RPO and requesting credit, and because farmer characteristics that affect RPO membership can also affect access to credit, the logit analysis estimates relationships between two variables that cannot be understood as causal.

[26] Value estimated as the exponential of the RPO membership coefficient (0.933) in the specification without the complete set of controls (column 1), which has a much larger N.

Table 1. Logit model: Individual access to credit

	Requested credit (probability of credit demand)		Received the requested credit (probability of credit supply, conditional on demand)	
VARIABLES	(1)	(2)	(3)	(4)
RPO member	0.933***	0.836***	0.210***	0.195***
	[0.028]	[0.027]	[0.032]	[0.031]
Received Technical Assistance	0.877***	0.769***	0.319***	0.295***
	[0.029]	[0.026]	[0.029]	[0.030]
Sells produce in the market	1.491***	1.031***	0.609***	0.485***
	[0.032]	[0.031]	[0.033]	[0.047]
Owns agricultural machinery	0.571***	0.448***	0.092***	0.087***
	[0.025]	[0.025]	[0.030]	[0.031]
Community org. member	0.051	0.089	-0.175***	-0.165***
	[0.051]	[0.054]	[0.052]	[0.057]
Male		0.285***		0.056**
		[0.017]		[0.026]
Above average age		-0.091***		-0.207***
		[0.012]		[0.021]
Finished primary		0.003		-0.231***
		[0.016]		[0.023]
Private health		-0.261***		-0.027
		[0.024]		[0.030]
Ethnic background		-0.433***		-0.010
		[0.115]		[0.118]
Constant	-3.873***	-3.342***	1.270***	1.503***
	[0.044]	[0.044]	[0.044]	[0.054]
Observations	2,259,298	1,068,983	250,230	155,910

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. Results are based on self-reports of credit request and access during 2013. The number of observations for the likelihood of credit supply conditional on demand is estimated only for farmers who requested credit. The estimates in columns 2 and 4 have fewer observations because additional controls are not reported for all farmers. A small share of agricultural productive units (UPA) had more than one head (leader). For these, age is the average age, while Finished primary and Private health were coded as 1 if at least one household head took that value.

We now turn to our main analysis, municipal-level estimates. Table 2 shows the relation between CA measured as the number of RPOs per thousand rural inhabitants and our two outcome variables. Columns 1-3 show results for total number of credits allocated (access to credit at the extensive margin) while columns 4-6 show results for total value of credits allocated (access to credit at the intensive margin). The coefficients of CA on both outcomes are positive and statistically significant. In our preferred specification, which includes only exogenous controls (columns 2 and 5), coefficients show increases in the number of credits allocated of 0.05 standard deviations, and in the value of credits allocated of 0.14 standard deviations. These results are robust to different sets of control variables, as seen in columns 1, 3, 4 and 6.

Table 2. FE estimations: Total number and value of credits

Dependent variable:	Number of credits (per capita)			Value of credits (per capita)		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
RPO (per thousand rural inhabitants)	1.204**	1.146**	1.679**	0.600***	0.315**	0.502***
	[0.563]	[0.574]	[0.687]	[0.189]	[0.123]	[0.165]
Rain shock (cms)		0.002**	0.001*		0.000	0.000
		[0.001]	[0.001]		[0.000]	[0.000]
Lag Local fiscal revenue (per capita)			-3.036***			0.921**
			[1.168]			[0.363]
Lag National transfers (per capita)			14.601***			-0.082
			[2.919]			[0.491]
Lag Homicides (per capita)			-1.130***			-0.019
			[0.271]			[0.028]
Constant	7.455***	3.760*	-4.838*	0.670***	0.243**	0.013
	[1.812]	[2.122]	[2.768]	[0.040]	[0.108]	[0.293]
Observations	15,615	14,373	11,980	15,615	14,373	11,980
R-squared	0.421	0.436	0.443	0.284	0.217	0.220
Number of Municipalities	1,117	1,115	1,077	1,117	1,115	1,077
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Department-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All monetary variables in real terms. Homicides per capita in logs. Estimations exclude the five principal cities in the country. Specifications with only municipal fixed effects, with municipal and year fixed effects, and with region-year fixed effects generate consistent results.

To analyse heterogeneity in credit patterns, we disaggregate allocations by small, medium and large farmers, and by public vs. private banks. Results in Table 3 show that the

CA coefficient for credit allocated (in both number and value) to small farmers is positive, but only for public bank credit. Coefficients are also positive for large farmers, but only for private bank credit. For medium-size farmers, CA is insignificant for public and private credit measured by both number and value of credits.

Table 3. FE estimations: Number and value of credits by type of producer and credit source

	Number of credits (per capita)						Value of credits (per capita)					
	Public credit			Private credit			Public credit			Private credit		
	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RPO (per thousand rural inhabitants)	0.007	0.005	1.094**	0.064*	0.015	0.053	-0.003	0.003	0.017*	0.366**	-0.018	-0.002
	[0.013]	[0.039]	[0.527]	[0.036]	[0.041]	[0.047]	[0.002]	[0.006]	[0.009]	[0.153]	[0.011]	[0.002]
Rain shock (cms)	-0.000	0.000	0.001*	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	1.094***	1.178***	3.686*	0.238*	0.363***	0.211**	0.029***	0.036***	0.061***	-0.045	0.002	0.007*
	[0.182]	[0.097]	[1.893]	[0.133]	[0.129]	[0.106]	[0.007]	[0.009]	[0.014]	[0.095]	[0.023]	[0.004]
Observations	15,455	15,455	15,455	15,455	15,455	15,455	15,455	15,455	15,455	15,455	15,455	15,455
R-squared	0.481	0.360	0.400	0.125	0.196	0.272	0.036	0.398	0.590	0.096	0.252	0.228
No. Municipalities	1,115	1,115	1,115	1,115	1,115	1,115	1,115	1,115	1,115	1,115	1,115	1,115
Municipality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Department-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All monetary variables in real terms. Estimations exclude the five principal cities in the country. Specifications with only municipal fixed effects, with municipal and year fixed effects, and with region-year fixed effects generate very similar results.

7. Robustness Checks

We carry out a series of robustness tests on our results. We first show that results are robust to the inclusion of 23 additional control variables that could affect the allocation of credit or RPO dynamics in a municipality, but that could not be included in the panel model due to data availability. When we include them in a cross-section estimation for census year 2013, results are robust (see Annex Table A3). We also check for robustness to alternative measures of CA, employing a measure of associational density (number of RPO members over total rural population)[27] rather than our main measure of RPOs per capita. This estimation is also carried with cross-sectional data for 2013, the only year for which this information exists.

We now present results for treated vs. untreated municipalities, following the model described in the empirical section. Table 4 shows that, consistent with the FE model, increases in the number of RPOs in a municipality are associated with increases in access to agricultural credit. CA coefficients are positive for both number and value of credits allocated, although for value of credits the coefficient loses significance at conventional levels. For number of credits the effect is equivalent to 0.12 standard deviations. Annex figure A2 plots coefficients and confidence intervals of the test of leads and lags of treatment adoption, showing that, as required, indicators for pre-treatment periods are not significant.

[27] Note that census data records self-reported participation in RPOs, some of which may be informal. This is different from our RPO data, which correspond to formal RPOs.

Table 4. Differences in treatment adoption estimation: Total number and value of credits

Dependent variable:	Number of Credits (per capita)			Value of Credits (per capita)		
VARIABLES	(1)	(2)	(3)	(5)	(6)	(7)
Increase in RPOs $_{i,t}$	2.972***	2.960***	2.379**	0.189	0.191	0.189
	[1.117]	[1.128]	[1.137]	[0.200]	[0.202]	[0.182]
Rain shock (cms)		0.004***	0.004***		0.000*	0.000**
		[0.001]	[0.001]		[0.000]	[0.000]
Lag Local fiscal revenue (per capita)			-3.390***			1.674*
			[1.046]			[0.884]
Lag National transfers (per capita)			7.760***			-0.043
			[2.605]			[0.177]
Constant	5.476***	2.925***	2.641**	0.067	0.009	-0.038
	[0.696]	[1.073]	[1.081]	[0.043]	[0.065]	[0.082]
Observations	7,392	7,268	7,244	7,392	7,268	7,244
R-squared	0.303	0.317	0.326	0.095	0.096	0.139
Number of municipalities	528	526	526	528	526	526
Municipality FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Region-year FE	YES	YES	YES	YES	YES	YES

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All monetary variables in real terms. Estimations exclude the five principal cities in the country. We include Region-year fixed effects instead of Department-year FE as the sample is smaller and in around one-third of departments includes fewer than 5 municipalities. We do not include homicides in the set of socioeconomic controls due to missing values that would reduce the number of observations by more than half.

Finally, Table 5 presents the results exploiting differences in treatment timing, disaggregating data by farmer size and credit source. Results for credit allocated to small farmers are consistent with the FE model (positive for public credit). For credit allocated to large farmers, private credit is positive but insignificant at conventional levels. For the value of private credit allocated to medium farmers, the coefficient is negative and significant at the 10% level. Annex figures A3, A4 and A5 present results for lead and lags tests for these estimations, and support their validity.

Table 5. Differences in treatment adoption estimation: Number and value of credits by producer type and source

	Number of credits (per capita)						Value of credits (per capita)					
	Public credit			Private credit			Public credit			Private credit		
	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small	Large	Medium	Small
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Increase in RPOs $_{i,t}$	-0.014	0.003	3.029***	0.041	-0.078	0.017	-0.006	0.008	0.063***	0.154	-0.024*	-0.001
	[0.038]	[0.185]	[1.074]	[0.041]	[0.052]	[0.076]	[0.004]	[0.014]	[0.018]	[0.200]	[0.013]	[0.001]
Rain shock (cms)	-0.000	0.000	0.004***	-0.000	0.000	-0.000	0.000	0.000	0.000***	0.000	0.000	-0.000
	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	1.412***	-0.011	0.941	0.352***	0.169***	0.076	0.017***	0.003	-0.010	-0.009	0.007	0.002
	[0.094]	[0.146]	[1.012]	[0.042]	[0.053]	[0.108]	[0.007]	[0.010]	[0.013]	[0.054]	[0.013]	[0.001]
Observations	7,268	7,268	7,268	7,268	7,268	7,268	7,268	7,268	7,268	7,268	7,268	7,268
R-squared	0.259	0.177	0.293	0.025	0.068	0.154	0.006	0.231	0.484	0.010	0.106	0.076
No. Municipalities	526	526	526	526	526	526	526	526	526	526	526	526
Municipality FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All monetary variables in real terms. Estimations exclude the five principal cities in the country. Results are robust to the inclusion of controls. This table presents our preferred specification, controlling for rain shocks.

8. Discussion

Two main results flow from our analysis. First, there is a positive relation between CA and access to credit at both the individual (farmer) and locality (municipality) levels. Second, this relation is heterogeneous, depending on farmer size and credit source. The first result suggests that while RPO membership increases a farmer´s likelihood of accessing credit, increases in access do not crowd out credit resources available to non-members. In other words, there is an aggregate (local-level) increase in access to credit, rather than a re-composition of credit between members and non-members. Hence, this form of collective action can help spur local financial development, generating positive spillovers for the entire community.

The second result highlights the relevance of analysing heterogeneities in the distributional effects of CA. What explains the heterogeneous differences in increased access to credit? A first explanation could be heterogeneity in the type of farmer that participates in RPOs and exploits its benefits. If this were the case, RPO participation rates should be significantly higher for small and large farmers than for medium-size farmers. But this is not the case. Participation rates are 10% for small, 11% for medium and 12% for large farmers.

A second explanation is that the relation between CA and access to credit is bounded by pre-existing contextual conditions, in this case by the structural segmentation of the credit market across farmer types and credit sources. As discussed in section 2, private credit tends to be biased towards large farmers, whereas public credit tends to be biased towards small ones, leaving medium farmers in "the missing middle" (United Nations 2006). Our results show that CA replicates this existing market segmentation, rather than counteracts it.

We probe this issue further by disaggregating our logit model by farmer type and source to analyse differences in both the likelihood of requesting credit (demand) and the likelihood of receiving the requested credit (supply). The results, presented in Annex Tables A4 and A5, show that RPO membership appears to generate a demand-side effect for small farmers, increasing their likelihood of requesting credit. As discussed above, this may be because RPO membership helps increase small farmers' productivity and output (e.g. by accessing financial or technical support from public programs), leading to larger investment needs. We further find that RPO membership increases the likelihood of small farmers receiving the credit they request (a supply-side effect). In line with municipal-level analysis, this effect is larger for the likelihood of receiving public credit. This suggests that the CA effect is not sufficiently strong to counteract the structural biases that private banks have against small transactions. Indeed, census data shows that among small-farmer RPO members, 20% have access to public credit whereas only 5% have access to private credit.

Should we worry about small farmers having poor access to private credit? Benson (2019) documents that small farmers do demand private credit, among other reasons, because of its speedier approval time (less than a week, compared to a month or more for public credit). Credit timing is determinant in the borrowing decisions of farmers, as agricultural investments have set times based on production and weather cycles. Indeed, rapid disbursement is amongst the main reasons farmers turn to high-cost financial alternatives, such as microfinance and money lenders. Improving small farmers' access to private credit would likely produce positive development outcomes for them and their communities.

Turning now to large farmers, results in Annex Tables A4 and A5 indicate that RPO membership does not increase the likelihood of receiving the requested credit (i.e. there is no supply-side effect). This is likely because large farmers already face low supply-side credit constraints, leaving CA little scope to reduce them further. For instance, banks already see large farmers as creditworthy, attractive clients irrespective of RPO membership. There is, however, a demand side-effect: RPO membership increases the likelihood that larger farmers request credit. This is unlikely to be due to lower transaction-cost constraints associated with information sharing, as large farmers are not constrained by human and financial capital requirements.

A more likely explanation is that RPO membership increases large farmers' demand for large investments, perhaps linked to large productive activities that are undertaken collectively (e.g. a joint fruit processing unit), requiring large investments that they have to meet through credit rather than self-finance.[28] Consistent with municipal-level analysis, the CA coefficient on the likelihood of large farmers requesting credit is larger for private credit, probably because large credit demands are mainly met by private banks (average credit size to large farmers by private banks is 6.4 times larger than those from the public bank). Again, this result suggests that CA is replicating the structural segmentation of private credit in favour of large operations. From a development perspective, this contributes to high levels of rural financial inequality; large farmers constitute 1.2% of all farmers but receive 43% of total credit and 67% of total private credit.

Finally, regarding medium-size farmers, logit results show that RPO membership does not affect farmers' likelihood of receiving credit (i.e. no supply-side effect), but the coefficient for requesting credit (i.e. demand-side effect) is positive and significant. This suggests that while CA increases the credit demand of medium-size farmers, it is not sufficient to lessen the structural supply-side constraints they face. An illustrative example concerns banks' requirements for lending to medium farmers. The public bank requires them to present certified productive projects and financial accounts, as well as paying the cost of issuing a mortgage. Such costs can add up to US$ 200 per loan. In contrast, none of this is required for small farmers. These structural biases that CA does not appear to lessen likely have negative development consequences, as medium-size farmers have pent-up potential to grow and generate growth in the rural sector. Indeed, a recent study shows that the greatest impact of access to credit on poverty reduction occurs precisely in middle-income households (Bukari et

[28] Census data shows that large farmers request fewer credits than small farmers, suggesting that for regular sized investments, they tend to self-finance.

al., 2021).

9. Conclusion

Using data on farmers and municipalities in Colombia, we show that there is a positive relation between collective action in the form of Rural Producer Organizations and access to agricultural credit. Our evidence implies that RPOs have the potential to ease access not only to input and output markets, as previous studies have found (Desai and Joshi 2014, Verhofstadt & Maertens 2014, Vandeplas et al. 2013), but also to financial markets.

We show that CA generates heterogeneous effects for different groups, and that this likely derives from pre-existing contextual conditions binding the potential of CA as a development tool. CA's ability to ease access to agricultural credit depends on farmer size and on structural segmentation in credit markets. Both distributional and contextual conditions should be taken into account when studying CA, and when employing it in interventions as a development tool.

From a policy perspective, the results in this paper highlight the potential of using collective action to reduce credit constraints. To this end, CA organizations could be employed as formal, systematic sources of information to reduce problems of incomplete and imperfect information that banks face in rural areas, which limit credit allocation. For instance, banks could be encouraged to develop local alliances with RPOs to provide information on production conditions, commercialization opportunities, and important risks, in aid of their appraisal of productive projects. Banks could also rely on these alliances to identify and reach RPO members collectively, reducing search and allocation costs that make one-on-one credit allocations costly. RPOs could also provide reference letters to banks as screening tools, and act as intermediaries to collect payments, reducing operational costs as well as monitoring and enforcement problems. In this way, RPOs could help banks outsource relationship lending.

These alliances could be especially useful in rural areas lacking bank branches, where credit transaction costs can be far higher.

Banks could also rely on RPOs as diffusers of information on credit opportunities, and to offer financial education workshops that increase credit demand and improve its quality. RPOs could provide financial education workshops to members as well as non-members, profiting from their social networks, leadership and visibility.

Policy interventions could also rely on CA organizations to counteract the existing segmentation of credit markets that directs the public bank towards small farmers, private banks towards large farmers, and leaves the middle financially underserved. As mentioned above, private banks could use RPOs to allocate credit in blocks to several members at once, thus reducing fixed costs of small and medium transactions. In this way, RPOs could act as financial intermediaries that help to crowd-in credit resources that otherwise would not be granted to medium or small farmers. RPOs could also be encouraged as a tool for generating financial inclusion, by building informal credit histories of farmers before they request formal agricultural credit. This could be done by incentivizing RPOs to provide in-house loans, and group lending and saving schemes.

Further advancing our understanding of the heterogeneous effects of CA organizations, the spillovers they generate for non-members, and how their impacts are conditioned by contextual conditions might help developing countries promote CA in ways that improve rural welfare. More research is required to understand whether CA has the potential to reduce credit constraints in contexts where formal agricultural markets are less developed and credit constraints are more stringent.

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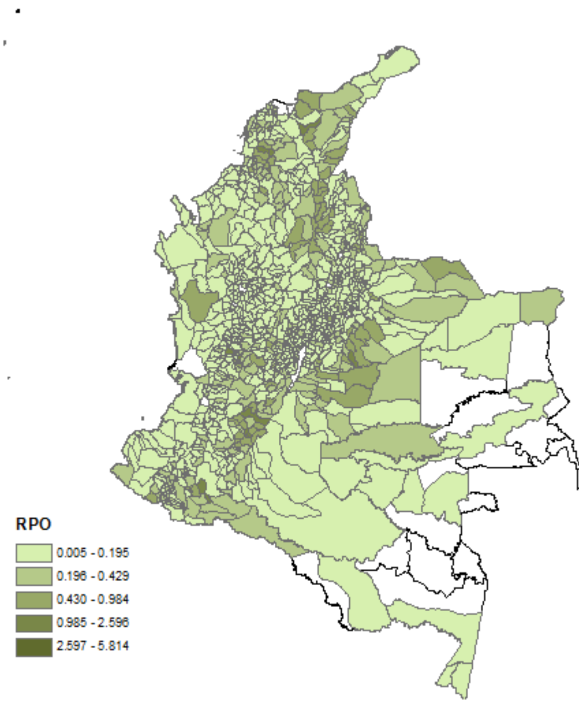
Annex

Table A1. Characteristics of credit granted by public and private banks

Category	Public credit	Private credit
Approval time	Weeks	Days
Interest rate	Low (around 1.2%)	Low (specially for large farmers)
Credit length	Long term credits (up to 10 years)	Long term credits (up to 10 years)
Requirements	Easy request process for small farmers	Less stringent mortgage requirements for large and medium farmers. Some allow wife to co-sign.
Main yype of clients	Small farmers	Small to large farmers
Geographic coverage	Large territorial presence	Some territorial presence
Cultural aspects	Tradition of being the agricultural bank (some farmers think it is the only one that lends for agricultural projects or the only one that grants incentives)	
Additional benefits	Incentives (ICR, LEC) and restructuring alternatives Can offer complementary public guarantee schemes	Incentives (ICR, LEC) and restructuring alternatives

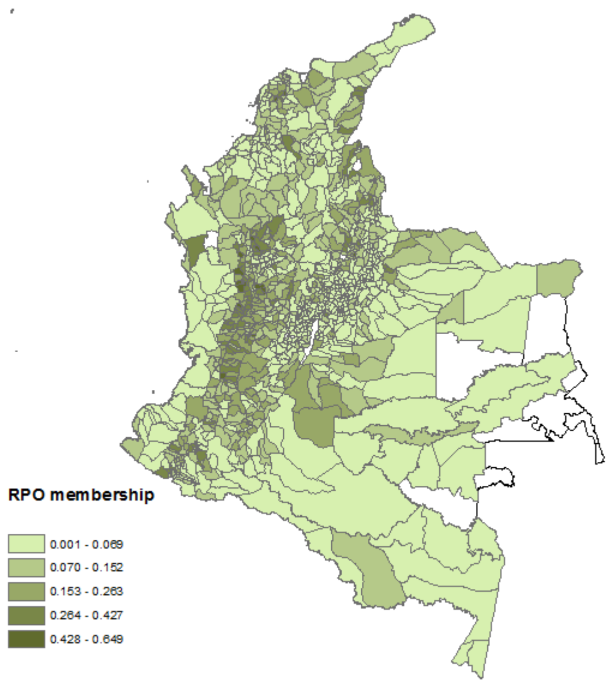
Sources: Authors' interviews and lenders' publicly shared credit guidelines

Map A1. Spatial distribution of RPOs (per thousand rural inhabitants) (2002- 2015)



Source: Author's estimations, based on RUES

Map A2. Spatial distribution of RPO membership (Share of producers who are RPO members)



Data source: CAN (2016)

Table A2. Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
MUNICIPALITY LEVEL DATA					
A. Independent variables					
RPO (per thousand rural inhabitants)	15,615	0.206	0.475	0.000	27.972
B. Dependent variables					
Main					
Value of credits (per capita rural) – COP real	15,726	0.789	2.326	0.000	132.845
Number of credits per thousand rural inhabitants	15,726	22.644	25.235	0.000	221.805
Farmer type and source *(per capita rural and real terms)*					
Number of public credits (large)	15,728	0.142	0.724	0.000	17.508
Number of public credits (medium)	15,728	2.196	3.500	0.000	42.058
Number of public credits (small)	15,728	18.438	22.839	0.000	206.076
Number of private credits (large)	15,728	0.179	0.811	0.000	24.379
Number of private credits (medium)	15,728	1.012	2.020	0.000	40.261
Number of private credits (small)	15,728	0.613	2.426	0.000	72.440
Value of public credits (large)	15,728	0.015	0.213	0.000	14.786
Value of public credits (medium)	15,728	0.147	0.319	0.000	7.863
Value of public credits (small)	15,728	0.231	0.381	0.000	5.177
Value of private credits (large)	15,728	0.228	2.0015	0.000	130.248
Value of private credits (medium)	15,728	0.155	0.420	0.000	9.003
Value of private credits (small)	15,728	0.0110	0.117	0.000	13.383
C. Control variables					
Rain shock (cms)	14,450	637.615	337.045	0.000	4368.8
Local fiscal revenue (per capita) -COP	13,114	0.180	0.373	0.000	14.198
National transfers (per capita) - COP	13,112	0.151	0.296	0.000	13.331
Homicides (per capita) (log)	10,238	-8.070	0.914	-11.998	-4.405

INDIVIDUAL LEVEL DATA					
D. Independent variables					
RPO member	2,366,192	0.098	0.297	0	1
E. Dependent variables					
Requested credit	2,366,192	0.107	0.309	0	1
Received credit	253,791	0.884	0.320	0	1
Requested credit – large farmer	2,366,192	0.001	0.033	0	1
Requested credit – medium farmer	2,366,192	0.012	0.108	0	1
Requested credit – small farmer	2,366,192	0.094	0.292	0	1
Received credit – large farmer	253,791	0.009	0.094	0	1
Received credit – medium farmer	253,791	0.094	0.291	0	1
Received credit – small farmer	253,791	0.782	0.413	0	1
F. Control variables					
Received Technical Assistance	2,366,192	0.166	0.372	0	1
Sells produce in the market	2,366,192	0.731	0.443	0	1
Owns agricultural machinery	2,299,590	0.164	0.371	0	1
Community org. member	2,263,394	0.054	0.226	0	1
Male	1,383,503	0.748	0.434	0	1
Above average age	1,383,503	0.474	0.499	0	1
Finished primary	1,347,753	0.250	0.433	0	1
Private health	1,356,197	0.186	0.389	0	1
Ethnic background	2,364,023	0.136	0.342	0	1

Note: Monetary values in millions of 2002 real COP.

Table A3. Differences in means test: Municipalities in subsample for treated and non-yet treated municipalities

	Mean Not in sample	In sample	Difference
Local fiscal revenue (per capita) -COP	0.205	0.185	
National transfers (per capita) - COP	0.108	0.199	***
Homicides (per capita) (log)	-8.133	-8.053	
GDP per capita (COP)	11.614	10.897	
Rural Poverty (UBN Index)	50.230	53.661	***
Distance to Department capital	79.293	79.600	
Total resources of credit pc	0.947	0.641	***
Number of credit pc	22.82	23.15	
Municipalities	569	532	

Map A3. Subsample for treated and non-yet treated municipalities

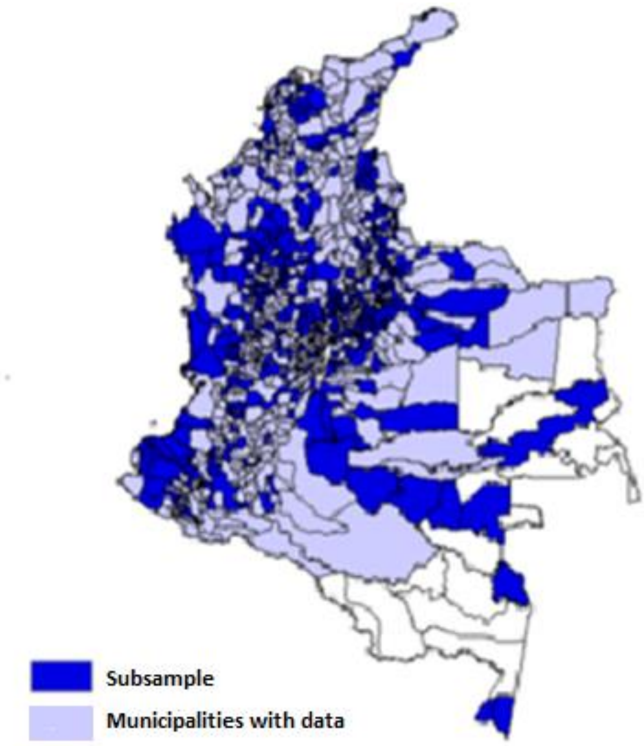


Figure A2. Number of municipalities without treatment (2002-2015)

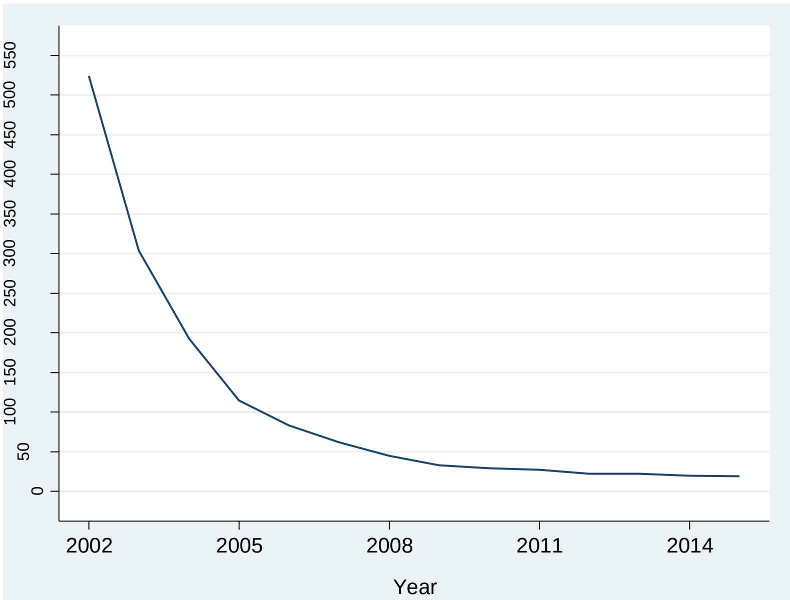


Table A4. Cross section results: Total number and value of credits granted per capita

	Total number of credits				Total value of credits			
VARIABLES	(1)	(2)	(3)	**(4)**	**(5)**	**(5)**	**(7)**	**(8)**
RPO (per thousand rural inhabitants)	7.625***	6.898***	7.462***	8.396***	3.570**	3.676**	6.350**	6.218**
	[2.663]	[2.621]	[2.878]	[2.893]	[1.763]	[1.820]	[2.698]	[2.678]
Rain shock (cms)		-0.001	0.002	0.000		0.001	0.002	0.001
		[0.003]	[0.003]	[0.002]		[0.001]	[0.001]	[0.001]
Local fiscal revenue (per capita)			-3.229**	5.343***			3.206**	2.562*
			[1.291]	[1.752]			[1.268]	[1.374]
National transfers (per capita)			36.892***	21.320***			0.523	0.982
			[8.515]	[7.176]			[1.883]	[2.205]
Homicides (per capita)			-0.121	-1.404			0.554**	0.198
			[0.951]	[0.872]			[0.241]	[0.236]
Land quality index				-0.419				0.048
				[0.679]				[0.137]
Height				0.001				-0.000
				[0.001]				[0.000]
Distance to capital city				-0.023*				-0.004
				[0.013]				[0.003]
Distance to market				-0.029**				-0.003
				[0.012]				[0.002]
Gini Index				-10.676				0.917
				[8.903]				[2.287]
Poverty (UBN)				-0.234***				0.003
				[0.053]				[0.014]
Fiscal performance index				-0.162				0.025
				[0.170]				[0.036]
Public Investment/ expenditure				0.135				-0.111*
				[0.174]				[0.061]

Received Technical Assistance				20.372***				4.574**
				[6.719]				[2.129]
Commercial activity				5.428				1.977
				[6.869]				[2.370]
Owns agricultural machinery				11.923				0.254
				[7.485]				[1.988]
Community organization member				-3.405				-4.243
				[7.993]				[2.823]
Medium farmers share				-22.967***				1.477
				[7.347]				[1.845]
Large farmers share				-3.460				10.534**
				[16.215]				[5.051]
Male				-5.513				-3.512
				[11.518]				[2.594]
Above average age				7.463				-0.717
				[11.969]				[4.862]
Finished primary				-69.993***				-3.062
				[10.364]				[2.827]
Private health				-41.386***				1.494
				[7.689]				[2.530]
Ethnic background				-18.193***				1.116
				[3.699]				[1.843]
Constant	32.062***	33.254***	21.849**	55.971***	1.563***	0.878	3.386	9.611
	[0.999]	[1.915]	[8.797]	[20.933]	[0.334]	[0.671]	[2.098]	[6.029]
Observations	1,117	1,082	820	795	1,117	1,082	820	795
R-squared	0.014	0.012	0.099	0.407	0.064	0.068	0.194	0.229

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. All monetary variables in real terms. Homicides per capita in logs. Gini and poverty values correspond to 2005. Estimations exclude the five principal cities in the country.

Table A5. Logit model: Individual access to credit by producer type

	Probability of credit demand			Probability of credit supply conditional on demand		
VARIABLES	Large	Medium	Small	Large	Medium	Small
RPO member	0.559***	0.590***	0.803***	0.041	0.022	0.089***
	[0.091]	[0.036]	[0.030]	[0.092]	[0.042]	[0.032]
Received Technical Assistance	0.069	0.092**	0.838***	-0.422***	-0.470***	0.444***
	[0.108]	[0.044]	[0.029]	[0.114]	[0.047]	[0.036]
Sells produce in the market	2.060***	1.727***	0.939***	1.562***	0.914***	0.015
	[0.284]	[0.079]	[0.033]	[0.384]	[0.091]	[0.046]
Owns agricultural machinery	1.656***	1.122***	0.275***	1.313***	0.851***	-0.472***
	[0.083]	[0.042]	[0.030]	[0.091]	[0.048]	[0.041]
Community organization member	0.370***	0.375***	0.029	0.13	0.281***	-0.253***
	[0.114]	[0.075]	[0.059]	[0.120]	[0.085]	[0.065]
Male	0.694***	0.535***	0.234***	0.497***	0.346***	-0.149***
	[0.085]	[0.033]	[0.019]	[0.094]	[0.030]	[0.023]
Above average age	-0.313***	-0.114***	-0.076***	-0.366***	-0.121***	-0.037*
	[0.060]	[0.024]	[0.013]	[0.063]	[0.025]	[0.020]
Finished primary	0.336***	0.080***	-0.017	0.331***	0.039	-0.176***
	[0.060]	[0.026]	[0.016]	[0.063]	[0.027]	[0.021]
Private health	0.930***	0.022	-0.328***	1.300***	0.350***	-0.314***
	[0.087]	[0.043]	[0.025]	[0.092]	[0.043]	[0.032]
Ethnic background	-0.836***	-0.795***	-0.358***	-0.559***	-0.465***	0.239*
	[0.173]	[0.130]	[0.122]	[0.170]	[0.152]	[0.127]
Constant	-10.110***	-6.613***	-3.345***	-7.501***	-3.580***	1.438***
	[0.296]	[0.096]	[0.046]	[0.398]	[0.107]	[0.053]
Observations	1,068,983	1,068,983	1,068,983	155,910	155,910	155,910

Robust standard errors in brackets clustered at municipal level. *** p<0.01, ** p<0.05, * p<0.1. Results are based on self-report of credit request and access during 2013. A small share of agricultural productive units (UPA) had more than one head (leader). For these, age is the average age, while Finished primary and Private health were coded as 1 if at least one household head took that value. We do not report results with a partial set of controls, but those are very similar.

Table A6. Logit model: Individual access to credit by producer type and source

Dependent variable: Probability of accessing credit by source and type of producer

	Public bank			Private banks		
	Large	Medium	Small	Large	Medium	Small
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
RPO member	0.332**	0.535***	0.719***	0.984***	0.655***	0.603***
	[0.136]	[0.041]	[0.031]	[0.101]	[0.058]	[0.057]
Received Technical Assistance	-0.018	0.104**	0.854***	0.432***	0.305***	0.560***
	[0.160]	[0.050]	[0.032]	[0.130]	[0.062]	[0.042]
Sells produce in the market	2.199***	1.852***	0.975***	2.580***	1.704***	0.975***
	[0.419]	[0.114]	[0.037]	[0.708]	[0.164]	[0.051]
Owns agricultural machinery	1.666***	1.156***	0.316***	1.705***	1.142***	0.110**
	[0.104]	[0.048]	[0.030]	[0.142]	[0.055]	[0.052]
Community organization member	0.431***	0.433***	0.066	0.005	-0.058	-0.266**
	[0.133]	[0.088]	[0.059]	[0.180]	[0.111]	[0.113]
Male	0.542***	0.537***	0.248***	0.792***	0.483***	0.194***
	[0.113]	[0.035]	[0.020]	[0.153]	[0.060]	[0.030]
Above average age	-0.070	-0.060**	-0.052***	-0.849***	-0.370***	-0.209***
	[0.073]	[0.026]	[0.014]	[0.101]	[0.043]	[0.019]
Finished primary	0.371***	0.001	-0.088***	0.290***	0.260***	0.121***
	[0.079]	[0.030]	[0.017]	[0.087]	[0.042]	[0.029]
Private health	0.475***	-0.188***	-0.486***	1.938***	0.636***	0.095**
	[0.101]	[0.048]	[0.029]	[0.117]	[0.059]	[0.038]
Ethnic background	-0.953***	-0.863***	-0.467***	-0.921***	-0.774***	0.009
	[0.187]	[0.163]	[0.129]	[0.228]	[0.149]	[0.200]
Constant	-10.662***	-7.223***	-3.905***	-12.543***	-8.445***	-4.995***
	[0.425]	[0.126]	[0.052]	[0.735]	[0.185]	[0.079]
Observations	1,068,983	1,068,983	1,068,983	1,068,983	1,068,983	1,068,983

Robust standard errors in brackets, clustered at the municipality level. *** p<0.01, ** p<0.05, * p<0.1. Results are based on self-report of credit request and access during 2013, for all the rural producers in Colombia. We do not report results with a partial set of controls, but those are very similar.

Figure A3. Leads and lags of treatment adoption: Total number and value of credits

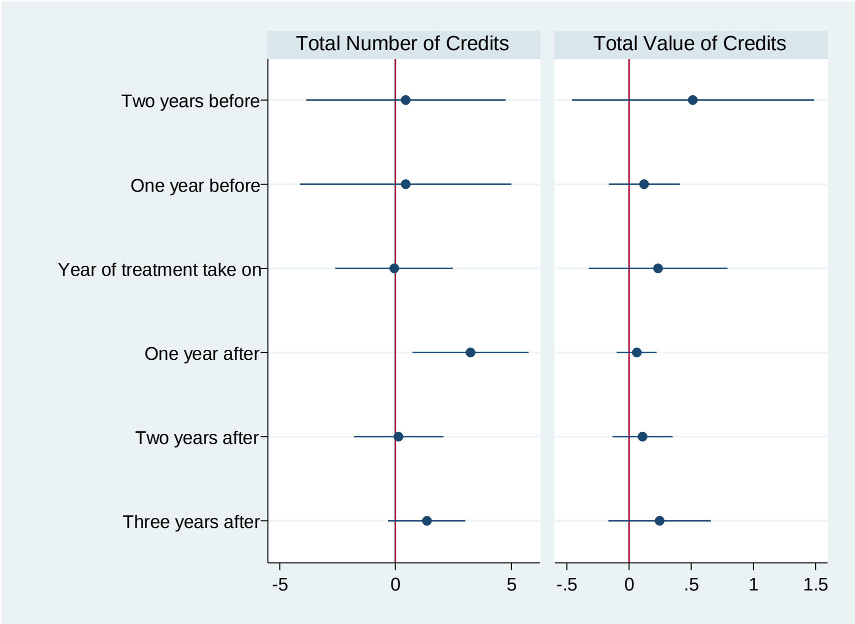


Figure A4. Leads and lags of treatment adoption: Total number of credits by producer type and source (Panel A, public credit - Panel B, private credit)

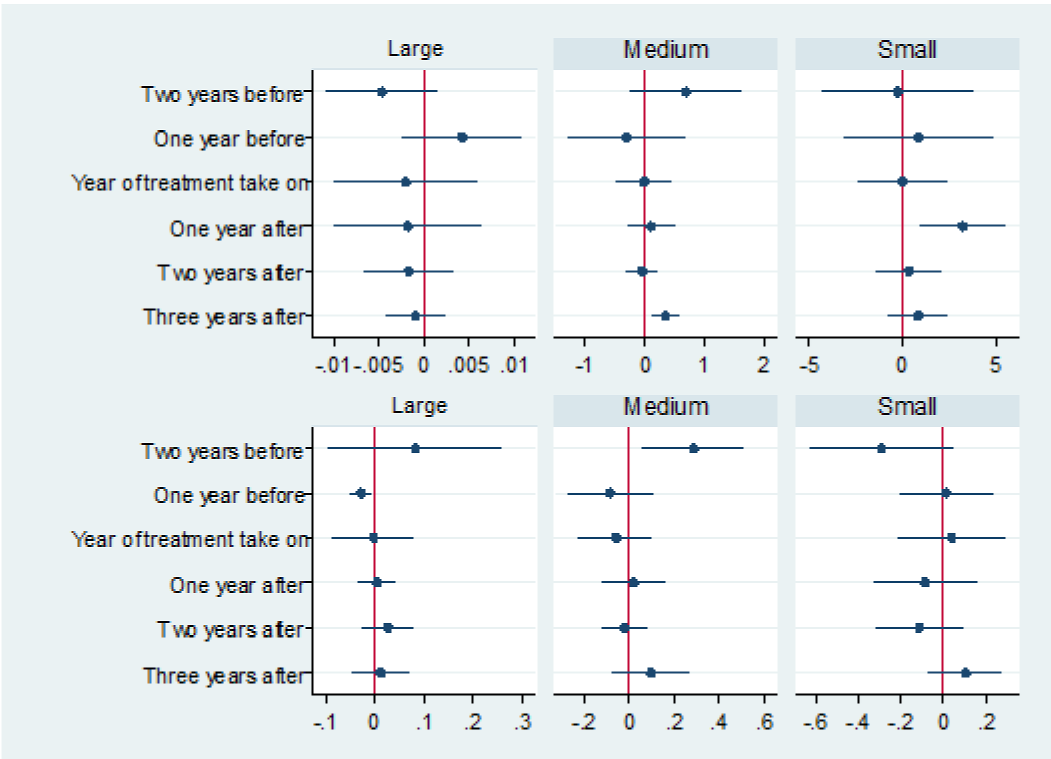


Figure A5. Leads and lags of treatment adoption: Total value of credits by producer type and source (Panel A, public credit - Panel B, private credit)