Forgone Investment:
Civil Conflict and Agricultural Credit in Colombia*

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Abstract

Do agricultural producers forgo otherwise profitable investments due to civil conflict? Answering this question is crucial to our understanding of the costs of violence, but requires the ability to measure farmers' willingness to invest and access to exogenous variation in conflict intensity. We exploit a unique administrative dataset from Colombia's largest agricultural bank and the 2016 demobilization agreement between the Colombian government and insurgent group FARC to overcome these challenges. A difference-in-difference analysis yields three main findings: First, credit to small producers increases after the agreement in municipalities with high FARC exposure (17% over sample mean). Higher loan applications drive this increase, with no change in supply-side variables. Second, a simple theoretical framework combined with rich information on characteristics of loan applicants and projects (including credit scores and loan outcomes) suggests that changes in project returns, but not in risk, underlie the increase in credit demand. Third, conflict is not the binding constraint on investment in areas with low access to markets. Higher investment, unchanged default rates and additional evidence of increased nighttime luminosity after the end of conflict imply an overall positive economic impact.

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1 Introduction

The disruption of investment decisions remains a little understood aspect of the economic costs of civil conflict. In particular, it remains unclear whether producers exposed to conflict forgo otherwise profitable investments, perhaps to avoid potential losses due to fighting or extortion by armed groups (Sánchez de la Sierra, 2020). Forgone investment could be a major obstacle to economic growth in conflict-ridden areas and may contribute to recurrent cycles of violence. Until now, the study of this topic has presented an insurmountable measurement challenge, as it can be difficult to distinguish a low willingness to invest from market imperfections limiting the supply of credit in rural areas (Banerjee, 2003; Conning and Udry, 2007). Furthermore, the non-random nature of conflict presents an additional challenge for identification. Armed groups predominantly operate in remote areas with weak enforcement of property rights and limited access to markets, factors themselves that hinder economic activity (Besley and Ghatak, 2010; Donaldson, 2018). Whether the end of conflict can lead to a tangible increase in investment under such conditions is far from certain.

In this paper, we study the effect of civil conflict on investment by Colombian farmers using granular credit data from the country's largest agricultural bank, *Banco Agrario de Colombia* (BAC). BAC is the only source of formal credit in many rural areas and our dataset includes the universe of the bank's business loans to small producers between 2009 and 2019 (2.9 million). These correspond to 1.7 million different applicants, equivalent to 64% of the country's agricultural producers. Besides its extensive coverage, our data has several unique features that facilitate the analysis. First, we observe credits starting at the application stage, which permits us to distinguish changes to the demand for credit from changes to the supply. Second, detailed information on applicants and loans, including credit scores, allows us to thoroughly characterize the sources of heterogeneity driving investment decisions and to study different potential mechanisms through which conflict may affect them. Third, multiple indicators on loan outcomes, including reports from in-person audits and default rates, enable us to detect changes to the quality of loans and potential misuse of funds.

Our empirical strategy leverages variation in conflict arising from the demobilization agreement signed by the Colombian government and Marxist insurgency FARC in 2016. FARC was the main guerrilla group fighting against the government in the civil conflict that ravaged the Colombian countryside for over 50 years, with an estimated death toll exceeding 200,000 victims (GMH, 2013). Using an event-based dataset, we calculate total FARC activity per municipality between 1996 and 2008 (i.e., before the start of our sample period). These were the most violent years in the history of the Colombian conflict. We classify municipalities as having high historical exposure to FARC if they rank in the top quartile of aggregate FARC activity per 10,000 inhabitants. Our research design compares credit outcomes between municipalities with high and low FARC exposure, before and after the end of the conflict, in a difference-in-difference framework with municipality and department-month fixed effects. The former account for persistent sources of heterogeneity affecting agricultural investment (e.g., geography), while the latter flexibly account for time-varying factors and allows them to differ across departments (e.g., macroeconomic shocks). Our preferred specification also includes time dummies interacted with a battery of pre-determined municipal characteristics, such as the rural share of population, and the share of land devoted to the cultivation of various different crops, including illegal narcotics. We also use LASSO regressions to optimally select the set of controls and estimate propensity-score weighted regressions to further address imbalance in covariates.

Our identifying assumption is that the difference in outcomes between municipalities with different levels of FARC exposure should remain stable in the absence of the demobilization agreement. We incorporate potential anticipatory effects by distinguishing between a *negotiation* phase and the period after the final *agreement* was signed in November 2016. We take an agnostic approach in defining the interim negotiations period and set its start date as June 2011, when Congress approved a landmark legislation allowing civilians affected by the conflict to receive reparations from the state and to seek restitution of land taken from them by force. This was arguably the earliest indication of the national government's renewed peace effort. We show that FARC municipalities experience a steady decrease in violence that starts in the negotiations phase and extends to the post-agreement period.

Our analysis yields three main sets of findings. First, we show that the end of the conflict leads to an increase in credit to small farmers in municipalities with high FARC exposure. We estimate a sizable increase of 19 million COP ($14,500 at the PPP-adjusted exchange rate) in total monthly credit disbursements per 10,000 inhabitants, equivalent to a 17% increase over the sample average. This increase is driven by higher loan applications, without any meaningful change in supply-side factors, including approval rates and interest rates. We also verify that the higher loan application rate is not driven by within-branch changes in the operation of BAC nor by geographic targeting by the government for post-conflict public spending. These results constitute *prima facie* evidence of higher willingness to invest in conflict areas after the demobilization agreement.

Second, we find that the increase in the demand for credit in FARC municipalities is disproportionately driven by new BAC clients with lower wealth and longer term investments (i.e., higher loan maturity). These results are consistent with the predictions of a stylized model of investment in which agents with CRRA preferences face heterogeneous investment opportunities. Importantly, we find no change in the average credit score of loan applicants, nor in delinquency rates for new or outstanding loans over various time horizons. These findings show that changes in project returns, but not in project risk, drive the observed changes in the demand for credit.

Third, we uncover significant heterogeneous effects across time and space. We find no evidence of an increase in credit demand during the interim negotiations period, despite a substantial de-escalation of the conflict. This suggests that armed group presence and uncertainty about renewed violence affect investment more than the contemporaneous intensity of conflict (Besley and Mueller, 2012). Additionally, we show that the increase in loan applications after the agreement is concentrated in FARC municipalities close to markets or urban centers. Conflict is not the main binding constraint on investment in remote and poorly connected areas. We also find that the increase in applications after the demobilization agreement is higher (though not significantly so) in municipalities with more informal land tenure or with a higher number of requests for land restitution after 2011. This suggests the presence of a complementary between access to land and the absence of violence in the investment decision.

Taken together, our findings point to a positive economic impact of the end of conflict in FARC municipalities. The fact that farmers are demanding more credit with no change in default rates suggests that these loans are providing capital for profitable investments. Moreover, reports from in-person audits of investment sites reveal no meaningful change in misuse of funds. Combined with the additional fact that the extra loans are disproportionately benefiting new and less wealthy clients, this arguably constitutes a successful expansion of BAC operations in conflict-ridden areas. As further evidence of a positive economic impact, we show that nighttime luminosity increases in FARC municipalities after the demobilization agreement. This result suggests that the end of conflict may also be leading to higher returns to investment via a broad expansion of local economic activity.

This paper contributes to the burgeoning literature on the economics of civil conflict (Blattman and Miguel, 2010). In recent years, this literature has made substantial progress in understanding the causes of violence (e.g., Dube and Vargas, 2013; Nunn and Qian, 2014; Berman et al., 2017). However, our understanding of the economic costs of conflict remains somewhat underdeveloped.[1] One line of work has documented negative effects of urban ter-

[1] A large literature has documented negative effects of conflict on human capital (e.g., Camacho, 2008; Akresh et al., 2012; Mansour and Rees, 2012; León, 2012).

rorism in developed countries (Abadie and Gardeazabal, 2003; Besley and Mueller, 2012). Another strand has found mixed results on the long-run impact of highly-asymmetric conflicts involving foreign superpowers (Miguel and Roland, 2011; Riaño and Valencia Caicedo, 2020). The idea that conflict may lead producers to forgo otherwise profitable investments has received little attention by the literature, except for a small number of studies documenting changes to productive activities and asset holdings as coping mechanisms amid conflict (Deininger, 2003; Verpoorten, 2009; Arias et al., 2019). These studies have largely relied on surveys and have generally struggled to establish causality. We add to this literature by using detailed administrative records from the largest agricultural bank in Colombia to document a sizable negative impact of civil conflict on willingness to invest. Our data provides a unique opportunity to precisely measure the impact of conflict on forgone investment, to disentangle demand and supply in the credit market and to characterize the sources of heterogeneity driving investment decisions and they way in which conflict affects them. Moreover, we exploit the FARC peace process as a natural experiment that allows us to credibly estimate the causal effect of conflict on investment.[2]

Our paper also speaks to the large literature studying the constraints faced by small-scale farmers in developing countries (Banerjee, 2003; Conning and Udry, 2007). This literature highlights how different forms of risk, such as weather variability (Rosenzweig and Wolpin, 1993; de Roux, 2020) or price fluctuations (Fafchamps, 1992; Burke et al., 2019), shape farmers' production and investment decisions. Previous research has also shown how financial market imperfections, highly prevalent in rural settings, lead to credit and risk constraints that hinder investment (Guirkinger and Boucher, 2008; Karlan et al., 2014; Cole et al., 2017). Our paper contributes to this literature by providing causal evidence on conflict as an additional and important constraint affecting a farmer's decision to invest. Furthermore, we provide evidence on the interaction between conflict and other factors affecting investment, such as access to markets or informal land tenure.

The rest of this paper is organized as follows. Section 2 provides background information on the Colombian conflict and BAC's credit operations. Section 3 introduces our main sources of data and discusses our empirical strategy. Section 4 presents our main results on loan applications and credit disbursements. Section 5 presents a simple model of investment to guide our discussion of mechanisms, which follows in Section 6. Section 7 discusses the implications of our findings for the broader economic impact of the end of conflict and provides additional evidence from nighttime lights, while Section 8 concludes.

[2]Our paper adds to a growing body of work on the effects of the agreement between FARC and the Colombian government (Namen et al., 2020; Prem et al., 2020a,b).

2 Background

2.1 The Colombian Conflict

FARC was a Marxist insurgent group created in 1964.[3] It originated from peasant self-defense groups dating back to the late 1940s, when intense political violence between the Liberal and Conservative parties swept Colombia. During its first two decades of existence, FARC operated in remote, rural areas, extorting local farmers and waging a low-intensity war against government forces. The group grew rapidly in the 1990s, particularly as its involvement with the drug trade increased, and had as many as 20,000 troops by the year 2000 (Dube and Vargas, 2013).[4] A series of FARC military victories prompted President Andrés Pastrana (1998-2002) to engage in peace negotiations with the group, which ultimately failed in 2002.[5] This was a period of heavy conflict involving FARC, government forces, and right-wing paramilitary groups, as panel (a) of Figure 1 shows. Pastrana's succesor, Alvaro Uribe (2002-2010), embarked on an intense military campaign against FARC that proved highly successful, leading to the death or capture of many FARC commanders and the rescue of its most high-profile hostages.

Uribe's successor, Juan Manuel Santos (2010-2018), started a new round of peace talks with FARC in September 2012. The announcement of a renewed peace effort was largely unexpected, as Santos had served as Secretary of Defense under Uribe and was elected on a hard-line, anti-insurgent platform. In the months preceding the announcement, the Colombian military had in fact killed FARC's top two commanders, *Mono Jojoy* and *Alfonso Cano*. However, Santos had begun to show signs of a renewed attitude toward Colombia's internal conflict in June 2011, when he signed into a law a *Victims bill* that allowed civilians affected by the conflict to seek reparations from the State. The bill also enabled people that were forcibly displaced from their land to seek restitution.

The new round of peace talks focused on a pre-arranged agenda containing five points. These were (i) rural development, (ii) political participation, (iii) end of hostilities, (iv) solutions to illegal drug trafficking, (v) truth and reparations for victims. The first part

[3]FARC is the acronym for Fuerzas Armadas Revolucionarias de Colombia (*Colombian Revolutionary Armed Forces*).

[4]In the UCDP/PRIO dataset, Colombia is classified as having a civil conflict (i.e. 25-999 battle-related deaths per year) continuously between 1964 and 1984. In the following two decades, 45% of years are classified as civil war (1,000 deaths or more).

[5]Previous peace talks took place during the governments of Belisario Betancur (1982-1986) and Cesar Gaviria (1990-1994). The Betancur process led to the creation of political party *Unión Patriótica* as a FARC offshoot, which was targeted and decimated by right-wing paramilitary groups in the following years (Fergusson et al., 2020). The Gaviria peace talks were also unsuccessful.

of the negotiations took place amid continued fighting, except for a handful of short-term ceasefires on occasions such as Christmas or the 2014 Presidential elections, when Santos was re-elected for a second term. Ongoing hostilities led to multiple incidents and to several suspensions of the negotiations. Still, agreement over the first two points was reached in 2013, over drug trafficking in 2014, and over victims in 2015. Despite progress on the negotiation agenda, the talks took place under the premise that a partial agreement was not feasible, which added uncertainty. The fact that several previous attempts at peace had failed also invited to prudence. In December 2014, FARC declared a unilateral ceasefire, which was reciprocated by the government in 2015. The negotiations were finally completed in June 2016, when an agreement was reached over the end of the conflict. The agreement was submitted for popular approval through a plebiscite held in October 2016. Narrowly rejected ("No" option won with 50.2% of votes), the agreement was partially modified to incorporate some of the concerns of its opponents. The modified agreement was signed by both parties in November 2016, putting an end to over 50 years of violence.

At the core of the agreement was FARC's commitment to lay down its weapons, withdraw from drug trafficking and contribute to peace through truth-telling, reparations and demining. In return, the government agreed to provide temporary economic support to former combatants and to award the group a handful of seats in Congress for two terms (starting in 2018 and 2022). A transitional justice mechanism was created to handle crimes committed by all parties during the conflict. The government also agreed to implement several policies aimed at rural development, including land redistribution and investments in infrastructure. A total of 170 municipalities in 16 different subregions were selected for inclusion in Post-Conflict Development Programs (*Planes de Desarrollo con Enfoque Territorial, PDET)* to guide these investments, but their implementation remains at an early stage. Though improved access to credit is mentioned in the sections of the agreement concerning rural development and illegal drugs (without mentioning BAC specifically), there is no evidence of changes in policy. Following the agreement, the vast majority of FARC members demobilized and the organization transitioned into a new political party that took part in elections in 2018 and 2019, with the exception of some small splinter groups.

2.2 Agricultural Credit

The Colombian Agrarian Bank (*Banco Agrario de Colombia*, BAC) was created in 1999 to replace a previous financial institution called *Caja Agraria*, dating back to the 1930s. It is a government-owned bank, overseen by the Ministry of Agriculture. Its bylaws state that at least 70% of its credit portfolio must be allocated to activities related to agriculture, livestock, fishing or forestry. BAC is the main and often the only source of financial services for people in remote, rural areas. In 2013, BAC was responsible for 97% of formal loans to small farmers (DNP, 2014). At the beginning of our sample period in 2009, there were 729 BAC branches in 710 municipalities. By the end of the sample in 2019, these numbers had risen to 780 branches in 754 municipalities.

Small producers typically apply for a loan at the BAC branch closest to them. The application process involves two stages. In the first stage, which usually takes place while the client is at the branch, a bank employee makes a query about the farmer to a credit bureau. The query results in a report that contains information on the credit history of the borrower and a credit score. It also indicates whether or not the application process can proceed.[6] Clients with no previous credit history skip this stage. In the second stage, the application is reviewed by a loan officer at BAC headquarters in Bogotá. Loan officers use different sources of information to make the final approval decision. An important input at this stage is a score from BAC's own credit-scoring models, which is different from the external score used in the first stage. The credit analyst also takes into account other aspects of the application like the projected income flow of the project and farmer characteristics.

Besides its intervention through BAC, the national government intervenes in Colombia's rural credit market in two other ways. First, it provides collateral to small farmers through the Agricultural Guarantee Fund (*Fondo Agropecuario de Garantías*, FAG). Farmers lacking sufficient collateral can request access to FAG when applying for a loan and bank officials determine the applicant's eligibility as part of the review process. Second, it provides subsidized funding for agriculture through the Agricultural Financing Fund (*Fondo para el Financiamento del Sector Agropecuario*, FINAGRO). FINAGRO is a second-tier public bank that lends *rediscount* resources to first-tier banks like BAC. In 2013, FINAGRO lent 87% of its rediscount resources to BAC (DNP, 2014). FINAGRO sets a cap to the interest rates that banks can charge for loans made with its resources, thereby allowing farmers to enjoy lower rates. Among the loans in our sample, 69% use funds from FINAGRO. Importantly, FINAGRO requires that 10% of loans using its funding be randomly selected for in-person visits to the investment site to ensure that funds have been used appropriately.

Once a loan has been disbursed, failure to make payments on time causes the applicant to

[6]The denial at this stage depends on a combination of the credit score, other variables in the credit history and certain BAC policies. For example, the application is rejected if the credit score is below a certain threshold or if the number of periods with overdues during past loan tenures exceeds a certain number. These thresholds and limits are periodically adjusted by BAC.

be reported to credit bureaus and the individual's credit history is negatively affected. In the scenario of complete default, BAC can reclaim the collateral. If the collateral is from FAG, the bank is fully covered, but in exchange must pursue legal restitution from the delinquent costumer, the proceeds of which return to FAG. A defaulting farmer is also no longer eligible for access to FAG resources in future applications. Therefore, farmers have a strong incentive to repay their loans even if they are not pledging most (or any) of the collateral.

3 Empirical Strategy

3.1 Data

Our main source of information are the administrative records at BAC. A unique feature of our setting is that we observe loans starting at the application stage and can track them throughout the approval, disbursement and repayment stages. This provides several advantages. First, we can disentangle the contribution of demand and supply to any observed changes in the amount of credit. Second, we can thoroughly characterize the pool of applicants and loans and detect changes in relevant characteristics. This allows us to analyze potential mechanisms through which conflict may lead to forgone investment and to characterize the underlying sources of heterogeneity that drive the investment decision. Third, we can study the quality of the loans by studying both default rates and the reports from randomized in-person visits of investment sites.

We collect data on all business loan applications by small farmers between 2009 and 2019. One reason why we focus on small farmers is because we are able to observe the destination municipality for all their applications, while we only observe the destination for fewer than 30% of loans to medium-sized and large producers.[7] Another more substantive reason is because small producers represent the bulk of BAC's clientele and are the ones that we expect to be most affected by conflict. Our sample includes 3.7 million applications and 2.9 million disbursed loans. These applications correspond to 1.73 million different individuals, which is equivalent to 64% of the total number of agricultural producers in Colombia, according to the most recent Agricultural Census in 2014. These loans amount to almost 22 trillion pesos (roughly 7.3 billion USD). For most of the analysis, we aggregate

[7] Throught the paper we use a nominal exchange rate of 3,000 COP/USD which is approximately the daily average exchange rate of 2017 and a PPP exchange rate of 1,315, the PPP exchange rate of 2017 according to the OECD. BAC defines as a small farmer one that has assets below 81 million pesos (approximately 27,000 USD). Also, either 75% or more of the farmer's assets must be dedicated to agriculture or at least two thirds of the farmer's income must come from agricultural activities.

outcomes at the municipality-month level (based on the destination municipality of each loan) and normalize by municipal population in 2008 (e.g., number of applications per 10,000 inhabitants). As part of our robustness checks, we use information on the bank branch where the loan originates and consider an alternative aggregation at the municipality-branch-month level. Appendix Table A1 provides summary statistics on our main outcomes of interest.

We measure exposure to FARC using an event-level dataset on the Colombian conflict provided by Universidad del Rosario. This dataset covers the period 1996-2014 and records conflict events (i.e. clashes, attacks) involving the different agents in the conflict (left-wing guerrillas, right-wing paramilitaries, government forces). For each event, the dataset records the location and the date of occurrence. The data is based on news reports from over 20 major newspapers, complemented with additional reports from NGOs and the Catholic church (Dube and Vargas, 2013). For our preferred measure of exposure, we first add all events taking place within the same municipality up to 2008 (i.e., before the start of the sample period) and normalize by population on that year. We then define as exposed to FARC the 281 municipalities that rank above the 75th percentile of this variable, similarly to Acemoglu et al. (2013). This measure captures historical exposure to FARC over a thirteen-year period that corresponds to the most intense phase of the Colombian conflict.[8] We verify below that our results are robust to (i) different thresholds for exposure, (ii) different duration of the exposure period, (iii) use of the continuous measure of exposure, or (iv) use of conflict data from an alternative source. Since our main conflict dataset ends in 2014, we use complementary data from the government agency charged with implementing the Victims Bill (*Unidad para la Atención y Reparación Integral a las Víctimas*, UARIV) that extends to 2018 to study conflict during our sample period. UARIV keeps a detailed registry of victims of the conflict and provides information on the type, location and date of each victimization event. Unfortunately, this data does not specify the armed group involved.

The maps in Figure 2 show the spatial variation in our measures of exposure to conflict and demand for credit. Panel (a) uses different colors for each quartile of the loan application rate during the sample period, while panel (b) shows the location of the municipalities exposed to FARC in the pre-period. Cross-sectionally, the correlation between FARC exposure and demand for credit appears to be negative. The loan application rate is highest in municipalities located in the mountainous chains near the center of the country, while FARC

[8]Though the relationship between armed group presence and violence may be non-monotonic, this is much more of a concern in studies that have as a primary objective to track insurgent activity over time (Crost and Felter, 2019). In our setting, it seems unlikely that a municipality with (true) high historical exposure to FARC will have few conflict events between 1996-2008, when the organization was at its peak.

municipalities are mostly located in jungle areas in the southeast and the Pacific coast, as well as in border regions near Ecuador and Venezuela (Martinez, 2017).

Additional information on municipal characteristics (e.g., share of land per municipality dedicated to cultivation of different crops) is provided by CEDE at Universidad de los Andes. CEDE collects data from multiple sources, mostly government agencies.[9]

3.2 Research Design

To estimate the effects of conflict on investment, we use a Difference-in-Difference (DiD) strategy that compares municipalities with varying exposure to FARC, before and after the peace agreement. All our regressions include municipality and department-month fixed-effects. The former control for all persistent sources of heterogeneity across municipalities that may affect demand for credit (i.e., geographic characteristics). The latter account for time-varying factors that affect all municipalities in the country (e.g., macroeconomic conditions), as well as those that are specific to each department (e.g. change of governor).[10]

Our identifying assumption is that in the absence of the agreement we should not observe any relative change in the demand for credit in municipalities with historical FARC presence. An important feature of our setting is that it involves a gradual de-escalation of the conflict in the lead-up to the final peace accord. While our main focus of interest is the period following the definitive signing of the peace agreement in November 2016, events before that date could have affected farmers' beliefs about the prospect of peace and their investment decisions. More specifically, events such as the Victims Bill from June 2011, the announcement of the start of peace talks in September 2012, or the successful culmination of negotiations around specific points on the agenda could have led people to update positively on the prospect of peace. We adopt an agnostic strategy in defining this interim phase and divide the sample into the following three periods. The first, from January 2009 to May 2011, is a pure *pre-period* that covers the end of the Uribe administration and the start of the Santos government, which initially continued Uribe's military campaign against FARC. The second period (henceforth referred to as *negotiations*) runs from June 2011, when the Santos administration first revealed its predisposition towards peace by signing the Victims Bill, to October 2016.[11] The third period (which we call *agreement*) starts in November 2016, when

[9] In Appendix B we describe in more detail the data sets and variables we use in the paper. Appendix Table A2 presents summary statistics of municipality level variables for municipalities exposed and not exposed to FARC.

[10] Colombia has 32 departments and 1,122 municipalities. Our sample has universal geographic coverage.

[11] As part of our robustness checks, we verify that the results are robust to other partitions of the sample

the final agreement was signed and ratified, and runs until the end of the sample in December 2019. We use the following specification to capture changes in our outcomes of interest in municipalities exposed to FARC during either the negotiations or agreement stages:

$$y_{i,j,t} = \alpha_i + \delta_{j_t} + \beta_1 \text{FARC}_i \times \text{Negotiation}_t + \beta_2 \text{FARC}_i \times \text{Agreement}_t + X_{i,t} + \epsilon_{i,j,t} \quad (1)$$

where $y_{i,j,t}$ is an outcome of interest in municipality i located in department j in month t. α_i and δ_{j_t} are municipality and department-month fixed effects. These locations refer always to the destination of the loan. $\text{FARC}_i \times \text{Negotiation}_t$ and $\text{FARC}_i \times \text{Agreement}_t$ are the respective interactions of the time-invariant dummy for FARC exposure with the time dummies for the negotiation and agreement periods. The effect of the individual terms included in these interactions is absorbed by the municipality and department-month fixed effects. Our coefficients of interest are β_1 and β_2, which capture the change in municipalities exposed to FARC, relative to the pre-period. These coefficients are comparable and allow us to measure changes between the negotiation and agreement stages. $\epsilon_{i,j,t}$ is an error term that we cluster two-way by municipality and department-year following Cameron et al. (2011). This cluster structure allows for idiosyncratic correlation of the error term within a municipality over time (with no restriction), and between municipalities in the same department within the same year (i.e., at a higher temporal level than our unit of observation, which is monthly). The latter flexibly accounts for spatial correlation within departments.

$X_{i,t}$ is a set of time-varying controls that we introduce to flexibly account for the potential confounding effect of other factors. Conflict is not randomly assigned and it is to be expected that municipalities with high levels of FARC exposure are different at baseline. Appendix Table A2 provides sub-group averages across FARC and non-FARC municipalities for a wide range of variables measured before the start of the sample period. Not surprisingly, FARC municipalities have a smaller population, are more rural, and are also poorer according to various metrics. These municipalities also differ in the share of land devoted to the cultivation of several important agricultural products and have higher cultivation of coca, the main input in the production of cocaine. Per se, these differences do not invalidate our DiD design, which relies on the identifying assumption that any effect of these differences is stable, rather than nonexistent. However, time-varying effects of these factors, which are not captured by the department-month fixed effects, could potentially bias our estimates. For instance, changes in the price of agricultural products, or in trade or anti-narcotics policy

period. Importantly, our measure of FARC presence, as well as all control variables, use information until December 2008 (i.e., before the start of the sample period).

could differentially affect the demand for agricultural credit in the affected municipalities. In our preferred specification, we address this concern by including as additional controls month fixed effects interacted with: (i) dummies for quartiles of the share of rural population in 2008; (ii) dummies for varying percentiles of the share of land devoted to the 10 main crops in the country; (iii) a dummy for municipalities with positive coca cultivation.[12]

The variables included in our baseline controls correspond to some of the most intuitive sources of potential unobservable variation in the demand for credit. As an alternative approach, we use a LASSO regression (Belloni et al., 2014) to select the optimal controls that best predict FARC exposure and replicate the analysis including month fixed effects interacted with each of them. As yet another way of addressing covariate imbalance, we estimate a propensity-score weighted regression following Hirano and Imbens (2001).[13]

The granularity of the data allows us to also estimate a more flexible *event study* specification that captures monthly changes in the outcome in FARC municipalities. While the parallel trends assumption underlying our DiD design is essentially untestable, this specification allows us to check for pre-trends before our events of interest. It also allows us to better understand the dynamics of the effects. For this purpose, we use the following specification:

$$y_{i,j,t} = \alpha_i + \delta_{j_t} + \sum_{\tau \neq \text{May2010}} \gamma_\tau \text{FARC}_i \times \tau_t + \epsilon_{i,j,t} \tag{2}$$

where τ_t is a dummy equal to one for month τ. The coefficient γ_t captures the change in the outcome in municipalities exposed to FARC in month τ relative to an arbitrary omitted period. This specification includes the same set of fixed effects and baseline controls as equation (1). The error term is also clustered two-way by municipality and department-year.

[12]The 10 crops are coffee, rice, sugar cane, plantain, oil palm, yucca, potatoes, cocoa, beans and corn. For each crop, we calculate the average share of land per municipality dedicated to its cultivation between 2000-2008. For potatoes, rice, oil palm and coca, less than 25% of municipalities grow each one, so we simply use a dummy for any production. At least 40% of municipalities cultivate each of the other crops and we split the positive values into two same-sized groups, leaving the zeros apart. The only exception is corn, which is grown in 89% of municipalities and for which we use quartile-specific dummies.

[13]This procedure improves balance by first restricting the sample to the common support of the propensity score for FARC exposure and by weighting observations corresponding to non-exposed municipalities by the inverse of a non-parametric function of the propensity score. Hirano et al. (2003) show that this weighting scheme leads to efficient estimates.

4 Main Results

We begin this section by providing first-stage estimates of disproportionate changes in conflict intensity in FARC municipalities during the negotiations and agreement phases. We then present our main results on the effect of conflict on the demand for credit and disbursed credit. At the end, we discuss some additional robustness checks.

4.1 Conflict Intensity

Panel (a) in Figure 1 plots the aggregate number of FARC events per month between 1996 and 2014. The graph shows that insurgent activity had been declining for several years before the start of our sample period in January 2009. This decline reflects the success of the military campaign launched by the Uribe government against FARC after 2002. Also important was the demobilization of the counterinsurgent paramilitary groups between 2003 and 2006. But the graph also shows that FARC continued to pose a meaningful security threat during the early years of the sample period, including the months after the start of peace negotiations in September 2012. On average, there were 135 FARC attacks per year between 2010 and 2014. For example, a FARC ambush in Arauca caused the death of 15 soldiers in July 2013 (BBC News, 2013).

Unfortunately, our main conflict dataset from Universidad del Rosario ends in December 2014. This prevents us from tracking changes in conflict throughout the negotiation and agreement phases. To fill this gap, we rely on data from the Colombian government's Victims Unit, UARIV, extending to 2018. This agency provides event counts at the municipality level for 12 different conflict indicators, including kidnapping, acts of terrorism, sexual violence, forced displacement and homicide. The downside is that the data is only available at the yearly level and does not specify the actors involved. To avoid incorrect inference from multiple hypothesis testing, we focus on an aggregate index (family of outcomes) obtained by standardizing and averaging across outcomes, following Kling et al. (2007).

Panel (b) in Figure 1 shows estimates from a year-level version of equation (2) using this conflict index as dependent variable. We see that conflict intensity starts to decline in FARC municipalities after the start of peace negotiations in 2012, though the difference relative to 2009 is only statistically significant after 2014. Moreover, the reduction in violence appears to stabilize with the final agreement in 2016. Appendix Table A3 provides estimates of equation (1) for the conflict index, as well as disaggregate results for each conflict outcome. The estimates for the family of outcomes confirm that FARC municipalities experience a significant reduction in conflict intensity both during the negotiations and the agreement periods, though the latter effect is twice as large. This suggests that if the intensity of violence is the main mechanism through which conflict affects investment, then we should observe higher demand for credit in both the negotiation and agreement periods.

4.2 Loan Applications and Disbursed Credit

Columns 1-5 in Table 1 present estimates of equation (1) using the number of loan applications per 10,000 inhabitants as dependent variable. All columns include municipality and department-year fixed effects. To start, column 1 shows results from a simplified specification that only includes the $\text{FARC}_i \times \text{Agreement}_t$ interaction as regressor of interest. The estimate for β_2 indicates that municipalities exposed to FARC experienced a 2.3 unit increase in the monthly loan application rate after the final peace agreement in November 2016. This is a sizable increase, equivalent to 13% of the sample mean of 17.96 monthly loan applications per 10,000 inhabitants. It is also quite precise and is statistically significant at the 1% level.

Column 2 verifies that the previous results are not driven by time-varying effects of fixed characteristics that correlate with FARC exposure and may affect willingness to invest. For this purpose, we include as additional controls month fixed effects interacted with (i) dummies for quartiles of the rural share of population in 2008, (ii) dummies for varying percentiles of the average share of land dedicated to cultivation of the 10 main crops in Colombia between 2000-2008, (iii) a dummy for municipalities with any coca cultivation between 2000-2008. We find that the inclusion of this flexible set of controls leads to only a slight reduction in our estimate of β_2, which remains positive and statistically significant.

Column 3 shows results when we additionally include the $\text{FARC}_i \times \text{Negotiation}_t$ interaction (i.e., when we disaggregate the period before the agreement in two). Our estimate of β_1 indicates a 0.6 unit increase in the loan application rate in FARC municipalities during the negotiations phase, which is not statistically different from zero, while the estimate for β_2 increases slightly relatively to column 2 and becomes very similar to the baseline estimate in column 1.[14] The difference between β_1 and β_2 is statistically significant at the 0.1% level. This result suggests that reductions in conflict intensity do not affect willingness to invest as long as uncertainty about renewed violence remains. This is in line with previous findings by Besley and Mueller (2012) on the impact of conflict on house prices in Northern Ireland. To confirm this interpretation, Figure 3 shows estimates of equation (2), our event-study spec-

[14] Column 1 in Appendix Table A5 shows that the results are unchanged if we set the start of the negotiations phase to September 2012 (announcement of peace talks) instead of June 2011 (Victims Bill).

ification, using the loan application rate as dependent variable. The graph shows that loan applications in FARC municipalities remain relatively constant throughout the pre-period and the negotiations phase (coefficients are small and mostly indistinguishable from zero), but experience a systematic increase following the final peace agreement in November 2016.[15]

The specification in column 3 of Table 1 is our preferred specification for the remainder of the paper. Before turning to other outcomes, columns 4 and 5 provide additional evidence against the confounding effect of covariate imbalance.[16] Column 4 shows results when we replace the fixed characteristics in our baseline controls with the optimal set of predictors for FARC exposure, selected using a LASSO regression (Belloni et al., 2014). Column 5 replicates the analysis in column 3 restricting the sample to the common support of the propensity score for FARC exposure (0.05-0.75) and weighting control observations by a function of the propensity score (Hirano and Imbens, 2001). In both cases, the results look very similar to the ones from our preferred specification in column 3.[17]

Columns 6-7 look at the impact of the negotiations and the agreement on the amount of credit actually disbursed. The dependent variable in column 6 is the number of loans disbursed per municipality-month, while in column 7 it is the total amount of credit disbursed (in millions of 2019 Colombian pesos). Both outcomes are normalized by population in 2008. Column 6 shows that the higher demand for credit in FARC municipalities after the peace agreement leads to a comparable increase in the number of loans disbursed. More specifically, we find a small and insignificant effect in the negotiation phase, together with a 2.1 unit increase in the loan disbursement rate after the end of the conflict. This is equivalent to a 14% increase over the sample mean of 14.4. It is also equivalent to 90% of the observed increase in loan applications. Column 7 shows that *monthly* BAC disbursements in FARC municipalities increase by 19.1 million pesos per 10,000 inhabitants after the end of the

[15] The omitted month in the plot is April 2010. To facilitate interpretation, the solid line shows the three-month moving average of $\widehat{\gamma_\tau}$. Appendix Figure A1 provides an alternative visualization at the quarter level, while column 2 in Table A5 provides estimates of equation (1) at this higher level of temporal aggregation.

[16] Columns 3-4 in Appendix Table A5 show that the results hardly change if we expand our baseline controls to include month fixed effects interacted with either dummies for quartiles of 2008 population or dummies for municipal categories. The municipal categories are determined by the government and are a function of population and municipal revenue and have various effects on the functioning of local governments. These tests ensure that the results are not driven by differential trends associated with the size of a municipality.

[17] Appendix Figure A2 shows the distribution of propensity scores by actual FARC exposure. The first stage regressions of columns 4-5, that we use to predict FARC exposure based on predetermined municipality characteristics before 2008, use only predetermined characteristics without any missing values. Appendix Table A4 shows that the results are very similar if we use a larger set of covariates, even though this leads to a reduction in sample size due to missing values.

conflict. This is equivalent to a sizable 16.7% increase over the sample mean.[18] Based on the nominal exchange rate, this amounts to roughly \$6,400 extra credit per month, while the PPP-adjusted exchange rate yields an increase of around \$14,500. These results point to a positive economic impact of the end of conflict in FARC municipalities via higher willingness to invest. We return to this below when we study loan outcomes and provide additional evidence from nighttime lights.

4.3 Additional Robustness Checks

We subject our main results on loan applications to a battery of further robustness tests. We summarize the results here and leave figures and tables for the online appendix. First, Figure A3 replicates the analysis from our preferred specification as we change the threshold value of the distribution of total FARC events that we use to define conflict exposure (top quartile at baseline). For this purpose, we consider threshold values between the 31st percentile (corresponding to the extensive margin) and the 95th percentile. We find that the estimate of β_2 remains positive and significant throughout the distribution, while the estimate of β_1 is always smaller and mostly insignificant. Moreover, the estimate of β_2 increases with the value of the threshold, which suggests that the impact of the peace agreement on the demand for credit was larger in municipalities hit harder by FARC violence. Relatedly, column 5 in Table A5 shows that the results are unaffected if we use the continuous measure of FARC exposure, while column 6 shows that the results are also similar if we measure FARC activity using information from an alternative source, CEDE at Universidad de los Andes. Figure A4 additionally shows that the results are also robust to using shorter time windows (i.e. closer to the sample period) to measure FARC exposure. Finally, we verify in Figure A5 that the results are robust to the exclusion of any one department from the sample.

5 Mechanisms: Theoretical Framework

In this section, we introduce a simple formal model to analyze farmers' investment decision. This model guides the empirical analysis of the mechanisms. Despite being highly stylized, the model helps us to characterize different ways in which conflict may affect investment. It also helps us to characterize potential sources of heterogeneity driving the increase in the demand for credit observed in FARC municipalities after the peace agreement.

[18] We study the loan approval rate and average loan size as part of our analysis of mechanisms below.

5.1 Basic Setup and Comparative Statics

Suppose that a farmer has a Constant Relative Risk Aversion (CRRA) utility function that depends on wealth ($w > 0$) and on a risk-aversion parameter $\rho \geq 0,\ \rho \neq 1$:

$$u(w) = \frac{w^{1-\rho} - 1}{1-\rho}$$

The farmer is faced with an investment opportunity that pays $r > 0$ with probability $q \in (0,1)$ and fails (i.e. pays 0) with probability $1-q$. The cost of this investment is $c > 0$. At the beginning of the period, the farmer has exogenous wealth $w_0 > 0$. We assume that initial wealth is either too low or insufficiently liquid, such that the farmer must take out a loan of size $l > 0$ in order to invest. This loan has a cost equal to $b > 0$, which includes the principal, payment of interest at rate $i \in (0,1)$, and other application costs and fees ($a \geq 0$). We refer to $b(l(c), i, a)$ as the total cost of investment. If the project fails, the farmer pays a cost given by $k \geq 0$. This cost may reflect wealth directly used for the investment that is not recovered, assets that the farmer must sell in order to repay the loan, or assets pledged as collateral and lost due to the inability to repay the loan. It also reflects the reputational cost incurred from defaulting on the loan, such as a lower credit score.

If the farmer invests, her expected utility is:

$$E[u(w)] = q\left(\frac{(w_0 + r - b(l(c), i, a))^{1-\rho} - 1}{1-\rho}\right) + (1-q)\frac{(w_0 - k)^{1-\rho} - 1}{1-\rho}$$

If the farmer does not invest, her utility depends only on her initial wealth:

$$u(w) = \frac{w_0^{1-\rho} - 1}{1-\rho}$$

By equating payoffs, we obtain the following indifference condition:

$$q(w_0 + r - b(l(c), i, a))^{1-\rho} + (1-q)\,(w_0 - k)^{1-\rho} = w_0^{1-\rho} \tag{3}$$

Equation (3) provides straightforward comparative statics on the factors that affect the investment decision. All else equal, farmers are more likely to invest in projects with a higher return (r) or a higher probability of success (q). They are less likely to invest as the total cost of investment (b) or the loss from a failed project (k) increase. Farmers with higher risk aversion (ρ) are also less likely to invest. The CRRA utility function implies Decreasing Absolute Risk Aversion (DARA). Hence, higher initial wealth (w_0) will make the risky investment more attractive.

We can use these comparative statics to identify potential underlying sources of heterogeneity that determine why some people invest while others do not. For this purpose, we must distinguish between elements in the model that correspond to fixed parameters and those that are random variables (i.e. vary across individuals, investment projects, or municipalities). For example, the interest rate (i) can be taken as roughly constant in our setting, as BAC's ability to manipulate it is highly regulated and the bank's supply of credit appears to be almost infinitely elastic.[19] The random variables in the model give rise to (potentially multi-dimensional) threshold conditions that determine the investment decision as a function of the fixed parameters. For instance, it seems plausible that people face random variation in the investment options that become available to them, characterized by the triad $\{r, c, q\}$. Under this assumption, projects with a sufficiently low return (r) or a sufficiently high risk (low enough q) are the ones that would fail to materialize, all else equal.[20] Alternatively, people may differ in their level of risk aversion (ρ), such that those sufficiently risk averse abstain from investing on an identical prospect. People may also differ in their initial wealth (w_0), in which case those with sufficiently low wealth are the ones that abstain from pursuing an otherwise identical investment opportunity.

5.2 Investment Under Conflict

We can also use our stylized framework to characterize different ways in which conflict may affect the investment decision. To begin, the presence of armed groups could directly reduce the return on investment (r) through extortion or expropriation. This was a generalized practice in the Colombian conflict, as documented by Arjona (2016). If not directly, armed group presence could also indirectly reduce the return to investment through a reduction in local economic activity, perhaps because of restrictions on business hours, mobility or access to inputs (Amodio and Di Maio, 2017). In the model, if r is a random variable, conflict would shift its marginal density f_r downwards. As a result, projects that would otherwise have high enough return to be pursued become no longer profitable.[21]

[19] The assumption of a a highly elastic supply of credit by BAC, combined with the fact that it is by far the main source of credit for small agricultural producers in our setting allows us to abstract away from general equilibrium considerations.

[20] Assume, for example, that the only source of heterogeneity is the project return (r), with CDF given by F_r. Moreover, assume for simplicity that $k = w_0$ (i.e., farmer loses all initial wealth if the project fails). The indifference condition in equation (3) can then be written as $r^\star = w_0(1/q^{1/1-\rho} - 1) + b(l(c), i, a)$ and the farmer invests if $r \geq r^\star$, which occurs with probability $1 - F_r(r^\star)$.

[21] Conflict can also reduce the return to investment through its negative effects on human capital (Akresh et al., 2012; León, 2012). However, we see this mechanism as less relevant for the relatively short time

Conflict may also increase the cost of investment. This can occur, for instance, if conflict prevents BAC from opening branches in municipalities with armed group presence. If such, the cost of applying for a loan (a) would be higher for residents of these municipalities. It could also happen that the bank is more reluctant to lend money in conflict-ridden municipalities, perhaps because its ability to monitor investments is more limited there. This would correspond to a lower approval rate and, again, higher application costs (a). A related but somewhat different story involves changes in supply-side policies induced by the end of conflict. For instance, the national government could increase the supply of credit in conflict-affected areas as a way of fulfilling its commitment under the peace agreement to promote economic development in these areas. Such policies could be reflected in lower interest rates, BAC branch expansion or higher loan approval rates. In the model, these would also all correspond to reductions in the loan application costs (a).

Conflict can also increase the level of risk associated with an investment project, captured by the probability of failure $(1 - q)$. This effect could be related to extortion if armed group presence or territorial control fluctuates over time and if these groups behave like *roving bandits*, with short time horizons and very high expropriation rates (Sánchez de la Sierra, 2020). In this case, project success would require the realization of an additional event corresponding to armed groups not plundering the municipality. Alternatively, risk may also increase if events such as acts of terrorism or direct combat between insurgents and government forces may stochastically lead to the destruction of the object of investment (e.g., ruined fields or machinery).

5.3 Testable Implications

The empirical analysis of mechanisms that follows aims to establish the channels through which conflict leads to forgone investments (i.e., the treatment effect of conflict). It also aims to identify the people (or projects) whose investment decisions are affected by conflict and who drive the increase in the demand for credit after the peace agreement (i.e., the selection effect of conflict). In terms of our model, answering the first question entails pinning down the variables that change due to conflict (whether fixed or random), while answering the second question requires us to characterize the underlying sources of heterogeneity that determine who invests without conflict but otherwise would not.

To answer the first question on the treatment effect of conflict, we exploit detailed data on applicants and loans, as well as organizational information from BAC. With regard to the

horizon after the end of conflict that we are studying.

potential impact of conflict on supply-side factors, we use our difference-in-difference strategy to look at changes in loan approval rates or in the average interest rate charged to disbursed loans, among others. To study effects on the return to investment, we look at changes in the characteristics of loans, including their maturity and intended destination. For instance, loans with a longer maturity probably reflect projects with a longer time horizon, which arguably have a lower discounted present value. Our analysis of the potential impact of conflict on risk crucially relies on the fact that the probability of default is increasing in the probability of project failure. If conflict made investment riskier, our difference-in-difference strategy should reveal a decrease in default rates following the demobilization agreement.

To answer the second question on the selection effect, we analyze changes in the pool of applicants and loans, exploiting the fact that different assumptions about the underlying heterogeneity lead to different predicted changes in observable characteristics. For instance, if the underlying heterogeneity mainly corresponds to differences in risk aversion across individuals, we would expect peace to attract more risk-averse applicants. Though this is not something that we can directly observe in the data, we can look for differences in demographic characteristics that correlate with risk aversion, such as gender (Charness and Gneezy, 2012), education (Jung, 2015), or age (Dohmen et al., 2017). However, one additional challenge comes from the fact that changes in a specific characteristic may be consistent with heterogeneity in more than one dimension. For example, an increase in the share of women applying for BAC loans could reflect heterogeneity in risk aversion (ρ), but is also consistent with heterogeneity in the return to investment (r) if, say, female producers face greater kinship taxation by friends and relatives (Jakiela and Ozier, 2015). Information on multiple characteristics can help us to partially overcome this challenge.

The channel through which conflict affects investment and the underlying source of heterogeneity may or may not coincide. For instance, it could be that conflict mostly affects investment via higher risk, but that the main source of heterogeneity driving investment choice is variation in risk aversion across individuals. If such, the direct effect of conflict should be reflected in lower default rates, while the selection effect might be reflected in changes in demographic characteristics of borrowers that correlate with risk aversion. In general, the treatment effect of conflict should be reflected in *improvements* in observable characteristics after the peace agreement, while the selection effect should be reflected in a "*worsening*" of observables (e.g., riskier projects, poorer applicants). Hence, if the two channels operate through the same variable, their effects will tend to offset each other. Returning to risk as an example, the end of conflict could may lead to a higher probability of success, but the selection effect means that relatively riskier projects are the ones driving the higher demand for credit. While the former effect should lead to lower default rates, the latter effect should lead to higher ones. Again, we rely on the wealth of data available to us to distinguish between these possibilities. For instance, by looking separately at changes in default rates for new and outstanding loans.

6 Mechanisms: Empirical Evidence

Our empirical analysis of mechanisms proceeds in four stages. First, we examine potential changes in supply-side factors that may have led to reductions in the total cost of investment. Second, we study changes in the characteristics of loan applicants and disbursed loans to disentangle different potential treatment and selection effects of conflict. Third, we use credit scores and loan outcomes to measure potential effects on risk. Finally, we look at heterogeneous effects by municipal characteristics to better characterize the locations driving the higher demand for credit after the end of conflict. Overall, the analysis suggests that the increase in the willingness to invest is driven by changes to project returns (r in our model) rather than changes to project risk (q).

6.1 Supply-side Factors

Higher demand for credit in FARC municipalities after the peace agreement may have been facilitated by changes in supply-side factors. These changes could have been caused by BAC's adjustment to a more peaceful environment. They could reflect policy choices dictated by the national government as part of its post-conflict agenda, including the implementation of its commitment under the peace agreement to promote development in rural areas. In our model, any of these changes would correspond to decreases in the total cost of investment (b), which would make otherwise unprofitable projects become worth pursuing.

Table 2 provides evidence on some potential channels. In columns 1 and 2, we examine whether changes in BAC branch location help to explain our results on loan applications. As expected, presence of a BAC branch in the municipality is associated with increases in the application rate, while greater distance to the nearest branch has the opposite effect. However, our estimates of β_1 and β_2 hardly change with respect to the baseline results in Table 1 when we control for these factors.

Columns 3-5 study changes in BAC policies along other dimensions. The dependent variable in column 3 is the share of applications originating from BAC field officers. These are BAC employees that work outside of branches, and visit farmers to offer them loans. In column 4, the dependent variable is the loan approval rate, while in column 5 it is the average interest rate for disbursed loans.[22] Our estimates of β_2 are all small and insignificant, suggesting no meaningful change in these variables after the end of conflict. In the case of the interest rates this is unsurprising, as these are highly regulated by FINAGRO, the second-tier bank that provides funding for most BAC loans.

In column 6, we follow an alternative approach and collapse the data at the branch-municipality-month level. This enables us to flexibly control for unobservable changes in branch operation over time by including branch-month fixed effects. We also include branch-municipality fixed effects to account for time-invariant differences in the demand for credit across different destination municipalities within the same branch. The results for loan applications from this modified specification indicate that the branch-level loan application rate increases by 0.2 units in FARC municipalities after the peace agreement. This is equivalent to a 16% increase over the sample mean of 1.23, an effect size highly comparable to the one we obtain at the municipality level. The estimate of β_1 is less than half as large and the difference between β_1 and β_2 is statistically significant at the 0.1% level.

Finally, columns 7 and 8 look more specifically at the potential impact of the implementation of the peace agreement by the central government on the loan application rate. As mentioned above, the government's main tool to coordinate development policy in conflict-ridden areas was the designation of 16 different areas (comprising 170 municipalities) for the design and implementation of individual Post-Conflict Development Programs (*Planes de Desarrollo con Enfoque Territorial, PDET)*. In column 7, we include month fixed effects interacted with separate dummies for each of these areas and fail to observe any meaningful change on our estimates of β_1 and β_2. This suggests that neither the actual implementation of PDETs nor farmers' expectations of greater public investment are driving our results. Column 8 takes a more agnostic approach and restricts the sample period to coincide with the second term of the Santos administration, shutting down potentially confounding effects from other policies by previous or later governments.[23] The results are once again unchanged.

Taken together, the evidence in this section shows that the higher demand for credit in

[22]The change in sample size is due to municipality-months without any applications (columns 3-4) or disbursements (column 5) which we set to missing. Additionally, data on BAC field officers are only available until December 2017. Appendix Figure A6 shows that our main result of the effect of the agreement on loan applications is robust to changes in the month in which the sample period ends.

[23]In our main sample, the pre-period includes the end of the Uribe administration and the first half of Santos' first term, the negotiations phase includes the later half of Santos' first term, and the agreement period also includes the first 18 months of the government of Ivan Duque, Santos' successor.

municipalities with high FARC exposure after the peace agreement is not driven by changes in supply-side factors. In terms of our model, the end of conflict does not appear to have meaningfully changed the cost of investment (b).

6.2 Characteristics of Applicants and Loans

In this section, we study changes in the characteristics of loan applicants and disbursed loans. Changes to the pool of applicants or loans allow us to shed light on different channels driving the treatment and selection effects of conflict. They can also be of policy interest.

Table 3 examines the characteristics of loan applicants. Columns 1-3 use basic information available in all loan applications, while columns 4-8 use more detailed data from BAC's credit scoring models. Information from these models is only available since July 2012, so we can only study the impact of the peace agreement relative to the negotiation phase.[24]

Column 1 looks at the share of applicants who had never previously applied for a loan at BAC.[25] We find that the share of new monthly BAC applicants increases by 2.4 percentage points (pp) in FARC municipalities after the peace agreement (6% increase over the sample mean of 0.38). This indicates that the higher demand for credit is disproportionately driven by people who had not previously applied for a loan and suggests that the heterogeneity driving investment choice corresponds mostly to differences across individuals rather than across projects available to the same person.

Columns 2-4 look at basic personal characteristics of loan applicants, including gender, age and level of education. On average, 41% of loan applications are made by women, 39% by people with secondary education or higher, and the average age of applicants is 44. As mentioned above, changes along these dimensions could reflect differences in risk aversion that underlie investment choice or differential targeting by armed groups. The results in columns 2 and 3 indicate small and insignificant changes in the share of female applicants and in average age. Column 4 shows a 1.7 pp increase in the share of applicants with secondary education or higher (4.4% increase over sample mean). This is consistent with more educated people being more risk averse and thus less willing to invest under conflict (Jung, 2015).

[24] The smaller sample size in some of the regressions of Table 3 is also due to municipality-months without any loan applications. Appendix Table A6 shows that the estimate of β_2 for loan applications is very similar for the shorter sample starting in July 2012. Table A6 also shows that data from the credit scoring models is available for 83% of loans after this date due to gradual implementation, with slightly higher coverage in FARC municipalities after the agreement.

[25] For this purpose, we use data on loan applications dating back to 2005. Applications before 2009 do not specify the municipality of the investment, which prevents us from using them in our main analysis. Results on the share of new applicants are very similar if we define clients as new relative to the start of the sample period in 2009 or if we define clients as new based on disbursed loans rather than applications.

Alternatively, more educated people could also have more accurate risk perceptions or be more financially literate, which would reduce investment under conflict relative to those who are less educated and more overoptimistic (Lusardi and Mitchell, 2014).[26]

Columns 5-8 provide evidence on the economic characteristics of applicants. Column 5 shows that the reported assets of the average applicant decrease by 1.4 million COP in FARC municipalities after the agreement, equivalent to a 2.3% decrease relative to the sample mean of 59 million COP (roughly USD 20,000). In terms of our model, this is consistent with variation in initial wealth (w_0) driving investment choice and with people with lower wealth forgoing investments under conflict due to preferences with decreasing absolute risk aversion. The estimates for average income, previous work experience or property size are all negative, which suggests selection effects in line with the model's predictions, but they are quite small and statistically insignificant.

We study the characteristics of loans in Table 4. Columns 1 and 2 show that the end of conflict does not affect average loan size. This suggests that heterogeneity in the cost of investment (c) is not a major driver of credit demand. Column 3 looks at the share of loans with farmers' assets as collateral. This share increases by 2.7 pp in FARC municipalities after the peace agreement (11% increase over sample mean, significant at the 10% level). In our setting, applicants have an incentive to pledge their own wealth as collateral since doing so reduces loan application fees (a) and they are liable for delinquent loans irrespective of the source of the collateral.[27] However, farmers can often struggle to provide the necessary legal documents to be able to use their assets (e.g., land) as collateral. If property rights improved after the end of conflict, we would expect to observe an increase in the share of loans with own collateral as in column 3.[28] We return to this point below when we study the interaction between the end of conflict and claims for land restitution.

Columns 4-6 present results on the maturity of loans. We find that the share of loans with maturity of 3-5 years decreases by 3.1 pp in FARC municipalities after the peace agreement, while the share of loans with maturity of 6 years or more increases by 2.8 pp (11% increase over the sample mean of 0.26). These results are in line with survey evidence by Arias et al. (2019) showing that conflict leads Colombian farmers to shift to activities with shorter yields.

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[26] In our model, $\hat{q_H} < \hat{q_L}$, where $\hat{q_H}$ and $\hat{q_L}$ are the risk perceptions of people with high and low education, implies $r_L^\star < r_H^\star$ for the return to investment that leaves the farmer indifferent.

[27] As mentioned above, loans without own collateral are mostly backed by the national government through a fund called FAG. Access to FAG requires payment of a fee equal to 1% of the amount covered, plus VAT.

[28] An alternative interpretation involves moral hazard and credit rationing (Besley and Ghatak, 2010). However, collateral requirements are not a major barrier to access to credit in our setting, as reflected by the relatively low average share of loans with own collateral (25%). The fact that farmers are liable for delinquent loans irrespective of collateral also goes against this interpretation.

A higher maturity arguably corresponds to projects with a longer time horizon and a lower discounted present value (keeping loan size fixed). If so, these results are consistent with project returns (r) being heterogeneous and with their distribution being positively affected by the end of conflict, which pushes projects that were previously not profitable enough (i.e., with a long maturity and a low r) above the indifference threshold ($r^{\star}$).

Finally, columns 7-10 look at the intended use of the loan. We find no effect of the peace agreement on the share of loans used for working (vs fixed) capital or in the share of loans intended for agricultural projects. This suggests that conflict does not disproportionately affect certain types of investment, as defined by these broad categories.

Overall, the results in this section suggest that the end of conflict had a positive impact on the distribution of returns to investment (r). Higher returns allow farmers (especially those with lower initial wealth) to pursue projects that were not profitable enough amid conflict, mainly those with a longer time horizon. However, these findings could also be an indication of changes to the risk of investment (q) after the peace agreement. We turn next to measures of loan performance to provide direct evidence on changes in risk.

6.3 Loan Performance

In this section, we study potential changes in the credit score of applicants and in several measures of loan performance. To the extent that the probability of default is higher when investment fails, these indicators can help us to establish whether the end of conflict affects the riskiness of investment (i.e., the probability of success q in our model).

The dependent variable in column 1 of Table 5 is the average credit score of loan applicants.[29] The results indicate that there is no meaningful change in the level of ex-ante risk of loan applicants in FARC municipalities after the peace agreement. Column 2 exploits a unique feature of our setting, which is the fact that BAC is required to audit the investment sites of loan recipients. These visits provide first-hand information on the potential misuse of funds.[30] On average, 14% of audits reveal some irregularity, ranging from inconsistencies in values or quantities to complete absence of the investment or inability to produce receipts.

[29] The credit score comes from a credit bureau and is only available in the BAC data since July 2012. As mentioned above, all applications go through an initial check with a credit bureau, which provides a report including a credit score. Applicants lacking a credit history (i.e. no credit score) are fast-tracked for review by a loan officer. Appendix Table A6 shows that the share of applications that have a credit score (87% on average) does not change in FARC municipalities after the peace agreement.

[30] Information from these audits is only available since July of 2011, which leads to a smaller sample size and only allows us to compare the negotiations and agreement periods. Appendix Table A6 shows that the share of loans that are audited in FARC municipalities increases marginally after the peace agreement.

Audit reports usually include receipts and photographic records of the investment, which reduces the risk of collusion. The results in column 2 indicate that the share of visits with irregularities also remains unchanged in FARC municipalities after the agreement.

We turn next to delinquency rates. For this purpose, we calculate the share of disbursed loans per municipality-month that go 60 days past due at some point in the future.[31] This calculation can easily be confounded by compositional effects, as loans disbursed earlier are observed over a longer time period and hence have a higher chance of failing. We address this problem by restricting both the sample period and the time horizon over which we observe each loan, thereby ensuring that we observe all loans for the same amount of time. Columns 3 and 4 provide estimates of equation (1) for the share of loans that go 60 days past due in their first year or in their first two years, respectively. All point estimates are very small and statistically insignificant, providing strong evidence of no change in default rates. Figure 4 shows estimates of the event study exercise described by equation (2) using 60-day default over a two-year horizon as dependent variable and further suggests a null result.

Going back to our model, the previous null effect on delinquency rates could be a reflection of offsetting selection and treatment effects of conflict. If conflict makes investments riskier, we would expect a decrease in default rates after the peace agreement. But if projects differ in their probability of success, the increase in the demand for credit should come from relatively riskier projects that become profitable enough after the end of conflict, which would lead to a counteracting increase in default. This possibility seems unlikely, since the credit scores in column 1 are not picking up changes in applicants' level of risk. However, to further explore a potential treatment effect of the peace agreement, we use as dependent variable in column 5 the share of outstanding loans per municipality-month that are 60 days past due. This outcome allows us to pick up changes to default rates among all loans being repaid after the end of conflict, rather than just focusing on the performance of loans disbursed after the peace agreement. It is also a more common measure of delinquency in bank portfolios. Still, the estimates remain small and insignificant, further suggesting no change in default.

Taken together, the results in this section suggest that there is no meaningful link between conflict and risk in our setting. We find no evidence that the peace agreement affects the probability of default among outstanding loans. Furthermore, new loans in FARC municipalities after the agreement are also no more risky, as measured by in-person audits, credit scores and loan performance. We conclude that changes in risk are not driving the higher demand for credit.

[31] Appendix Table A7 shows that results are very similar if we use other default thresholds.

6.4 Heterogeneous Effects

The results in the previous sections suggest that the end of conflict increases the returns of agricultural projects. As an alternative approach to study the mechanisms, in this section we present results on heterogeneous effects of the end of conflict on credit demand based on fixed municipal characteristics. If the main mechanism is indeed related to the return of the project, we should observe larger effects in municipalities with factors correlated with high agricultural returns, like market access. This complementary analysis can also help us to identify the circumstances under which conflict is the binding constraint on investment.

To carry out this exercise, we divide the set of municipalities that we defined as exposed to FARC into two equally-sized groups (i.e. above and below the median) based on each heterogeneity variable that we consider. We expand equation (1) to provide separate estimates of β_1 and β_2 for FARC municipalities in the upper and lower half of the distribution for each variable (β_k^{high} and β_k^{low}, $k \in \{1, 2\}$). If needed, we rescale variables so that larger values (i.e. high) correspond to more desirable attributes.

Table 6 shows the results.[32] The dependent variable in all regressions is the loan application rate. The first set of sources of heterogeneity that we consider concern the proximity of FARC municipalities to markets or large urban centers. Specifically, columns 1-3 look at proximity to wholesale markets, the departmental capital or Bogotá. For all measures, we find that the effect of the end of conflict in FARC municipalities with high market access (β_2^{high}) is much larger and significantly different from the estimate for those with low access (β_2^{low}), which is small and insignificant. This suggests that conflict is not the main binding constraint on investment in remote and poorly connected areas.

Our theoretical framework can easily accommodate these highly heterogeneous effects. Proximity to markets or urban centers arguably reduces production and transportation costs, which corresponds to a lower value of the parameter c in our model. If farmers face heterogeneity in the return to investment (r), the difference in costs will lead to different values of the indifference threshold, $r^\star$. Lower costs imply a lower threshold and more investment, all else equal. If the end of conflict directly affects the return to investment (i.e., a positive treatment effect that shifts the distribution of returns to the right), the higher indifference threshold in FARC municipalities with low access to markets could lead to a much smaller increase in investment. Appendix Figure A7 provides a visualization of this argument.

[32] Appendix Table A8 shows the cross-sectional correlation of the different variables we consider. Most correlations run in the expected direction (e.g., municipalities with better access to Bogotá have higher scores in the development index). However, most correlations are moderate (i.e. smaller than 0.4 in absolute value), suggesting that these variables do not have the same information content.

Columns 4 and 5 look at the potentially complementary effect of land redistribution and improved property rights. In column 4, we classify FARC municipalities based on the total number of applications for land restitution (per 10,000 inh.) submitted as part of the implementation of the Victims Bill since 2011. The results for this variable should be interpreted with caution, as it is being measured during the sample period and could itself be affected by the peace process with FARC. Nevertheless, the estimates suggest that the increase in credit demand in the post-agreement period is concentrated in FARC municipalities with a high application rate for land restitution, though the difference between β_2^{high} and β_2^{low} is not significant at conventional levels (p=0.19). Column 5 further shows that the effect of the peace agreement is also higher in FARC municipalities with more informal land tenure before the start of the sample period. However, β_2^{high} and β_2^{low} are again not significantly different (p=0.44). Though this evidence is only suggestive, it could help explain the higher share of loans using own collateral documented above if applications for land restitution are leading to formal land titles in places with previously high levels of informality. It is also worth noting that the demand for credit in FARC municipalities with high applications for land restitution only seems to increase after the peace agreement, despite the fact that the Victims Bill dates back to June 2011 (it is, in fact, the date we use to define the start of the negotiations phase). This suggests that peace and access to land are complements for investment by small producers in these areas.

Finally, column 6 examines potential heterogeneity based on a development index defined as the share of municipal population in the 2005 census without unmet basic needs (i.e., relatively low poverty based on UBN). We find that the effect of the peace agreement is higher in FARC municipalities with lower poverty rates, though the estimates of β_2^{high} and β_2^{low} are once again not significantly different (p=0.22). Though also only suggestive, this result could indicate that the end of conflict has a larger effect on investment in FARC municipalities with better local public goods, which plausibly reduces the cost of investment.[33]

[33] Appendix Table A9 considers other potential sources of heterogeneous effects. Though differences are not statistically significant, we find that the increase in credit demand after the peace agreement is larger in municipalities not included in the Post-conflict Development Programs (PDETs) and also in municipalities not hosting the camps in which FARC cadres initially grouped during demobilization. We find no evidence of heterogeneous effects based on measures of soil quality or measures of activity by other armed groups. Appendix Figure A8 shows the effect of the peace agreement on credit demand is concentrated in FARC municipalities located in the Andean and Eastern regions, with no effect in the Caribbean, Pacific or Amazon.

7 The Economic Impact of Conflict

Our previous results suggest a positive economic impact of the end of civil conflict in municipalities with historical exposure to FARC. To recap, monthly credit disbursements increase by 19 million COP ($14,500 at the PPP-adjusted exchange rate) per 10,000 inhabitants in these municipalities after the final peace agreement, which is equivalent to a 17% increase over the sample mean. These loans disproportionately correspond to new BAC clients, clients with lower wealth, and projects with a longer time horizon. Moreover, they benefit a sizable fraction of farmers in Colombia and not just a small set of entrepreneurs. Importantly, we find no evidence of changes in misuse of funds or in delinquency rates. From BAC's perspective, this arguably constitutes a successful expansion of its operation in conflict-ridden areas. To the extent that farmers are voluntarily seeking out these loans and are being able to repay them, these loans would appear to be providing capital for profitable investment projects, which should have positive downstream economic consequences.

To further study potentially broader changes in economic activity after the peace agreement, we use data on nighttime luminosity (Henderson et al., 2012). For this purpose, we rely on nightlights data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), which is available since April 2012.[34] We aggregate the monthly VIIRS data from its original spatial resolution of 740 meters to the municipality level by calculating an area-weighted average across pixels located in the same municipality. We prefer to collapse the data from its original monthly periodicity to quarterly averages in order to minimize the impact of measurement error, but also provide results at the monthly level.

Figure 5 plots estimates of equation (2) at the quarterly level, using log lights as dependent variable.[35] We observe a clear and stable increase in nighttime luminosity in FARC municipalities following the peace agreement. The estimate of β_2 from equation (1) available in Appendix Table A10 indicates that lights increase by 14 log points (23 points at the monthly level). These are sizable increases in luminosity and suggest a boom to local economic activity in FARC municipalities after the end of the conflict. Though some of this increase may be a reflection of investment projects funded with BAC loans, the quick timing of the effect suggests this is not the main driver. Instead, the increase in lights is arguably

[34]The VIIRS sensor is mounted on the Suomi satellite launched in 2011. This sensor measures radiance over a relatively large range and has onboard calibration, which ensures that data is comparable over time and across space. Even though VIIRS represents a marked improvement over the widely used DMSP series that preceded it, analysis of this data must proceed with caution as its correlation with economic activity can be weak in rural settings (Gibson et al., 2021).

[35]Appendix Figure A9 shows the analogous figure at the monthly level.

capturing alternative channels through which the end of conflict is boosting economic activity. These may include the elimination of restrictions on mobility or business hours, as well as improved security and lower extortion, all of which could positively affect private consumption and lead to an economic expansion. In this regard, the increase in nighttime lights is consistent with the end of conflict indirectly increasing the returns to investment via an expansion of aggregate demand.

8 Concluding Remarks

In this paper we show that civil conflict leads small agricultural producers to forgo otherwise profitable investments. In our analysis, we use detailed microdata on the universe of loans from the largest agricultural bank in Colombia between 2009 and 2019 and we exploit variation in conflict resulting from the peace agreement between the Colombian government and insurgent group FARC in 2016. Our difference-in-difference research design compares municipalities with differential exposure to FARC violence before and after the agreement.

Our analysis yields three main findings. First, monthly credit disbursements to small producers increase in municipalities with historical FARC presence after the peace agreement. Our estimates point to a sizable impact, equivalent to a 17% increase over the sample mean. This increase is driven by greater willingness to invest and higher loan applications, with no change in a wide range of supply-side variables. Second, a simple theoretical framework combined with rich information on characteristics of applicants and projects suggests that changes in the returns to investment, but not in project risk, underlie our results. Third, the increase in credit demand is concentrated in municipalities close to wholesale markets and urban centers. This suggests that conflict is not the main binding constraint on investment in remote and poorly connected areas. Furthermore, credit demand does not increase during the interim negotiations period despite a substantial reduction in violence. This suggests that uncertainty about future conflict affects investment more than contemporaneous changes in conflict intensity. We also find suggestive evidence of a complementarity between peace and efforts at land restitution for victims of the conflict.

Our research design is not meant to capture the macroeconomic impact of the peace agreement, as the department-month fixed effects included in all of our regressions absorb any benefits common to all municipalities. However, our findings provide several pieces of evidence suggestive of a broadly positive economic impact. First, the fact that farmers are demanding more credit and are being able to pay back their loans suggests that these are funding profitable investments. Moreover, in-person audits of project sites (a unique feature of our data) indicate that farmers are generally using the funding for the declared purpose. Finally, the documented increase in nighttime luminosity in FARC municipalities following the peace agreement is consistent with a broad expansion of local economic activity, which arguably contributes to higher returns to investment and greater demand for credit.

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Table 1: Loan Applications and Disbursements

	Application rate					Disbursement rate	
						Number	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FARC_i$ x $Negotiations_t$ [a]			0.567	0.905	1.066	0.701	7.611
			(0.643)	(0.624)	(0.775)	(0.489)	(4.639)
$FARC_i$ x $Agreement_t$ [b]	2.325***	1.917***	2.308***	2.636***	2.609***	2.077***	19.112***
	(0.572)	(0.498)	(0.743)	(0.736)	(0.867)	(0.627)	(5.686)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	Yes	No	Yes	Yes	Yes
LASSO controls	No	No	No	Yes	No	No	No
Propensity score weights	No	No	No	No	Yes	No	No
Observations	148,104	148,104	148,104	148,104	99,924	148,104	148,104
R-squared	0.692	0.707	0.707	0.703	0.693	0.707	0.695
Mean DV	17.963	17.963	17.963	17.963	19.400	14.382	114.661
p-value H_0: [a] = [b]	-	-	0.000	0.001	0.005	0.001	0.001

Notes: The unit of observation is the municipality-month. The dependent variable in columns 1-5 is the monthly number of loan applications at BAC with intended destination to the municipality, normalized by population in 2008 (per 10,000 inhabitants). The dependent variables in columns 6-7 are the equivalent measures for the number of loans disbursed and the total amount of credit disbursed (in millions of 2019 COP). $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. All regressions include municipality and department-month fixed effects. Columns 2, 3, 5, 6 and 7 also include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Column 4 includes month fixed effects interacted with a wider set of controls selected using a LASSO procedure. Column 5 restricts the sample to municipalities in the common support for predicted FARC presence and weights non-FARC observations by a function of their estimated propensity score. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Loan Applications: Supply-side Factors

	Application Rate		Share of Applications		Average Interest Rate	Application Rate		
			Field	Approved				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$FARC_i$ x $Negotiations_t$ [a]	0.581	0.569	-0.027*	0.011*	0.071	0.071*	0.473	
	(0.641)	(0.640)	(0.015)	(0.007)	(0.348)	(0.042)	(0.666)	
$FARC_i$ x $Agreement_t$ [b]	2.397***	2.366***	0.020	-0.004	0.200	0.195***	2.274***	2.111***
	(0.740)	(0.738)	(0.018)	(0.007)	(0.425)	(0.050)	(0.786)	(0.535)
$\mathbb{1}$(BAC branch in municipality)$_{i,t}$	5.472***							
	(1.047)							
Distance to BAC branch (Km)$_{i,t}$		-0.292***						
		(0.053)						
Municipality FE	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Municipality x Branch FE	No	No	No	No	No	Yes	No	No
Branch x Month FE	No	No	No	No	No	Yes	No	No
PDET x Month FE	No	No	No	No	No	No	Yes	No
Presidential terms	All	All	All	All	All	All	All	Santos II
Observations	148,104	148,104	110,648	136,055	133,576	2,172,547	148,104	53,856
R-Squared	0.708	0.708	0.641	0.305	0.654	0.783	0.713	0.790
Mean DV	17.963	17.963	0.323	0.778	11.807	1.225	17.963	18.818
p-value H_0: [a] = [b]	0.000	0.000	0.000	0.000	0.645	0.000	0.000	-

Notes: The unit of observation in all columns except column 6 is the municipality-month. In column 6, the unit of observation is municipality-branch-month. The dependent variable is listed in the column header. In column 1, $\mathbb{1}$(BAC branch) is a time-varying dummy equal to one if a BAC branch operates in the municipality. In column 2, we replace this dummy with the distance between the municipality centroid and the nearest BAC branch in kilometers. In column 3, the dependent variable is the share of applications arising from field visits by BAC representatives to farmers (data only available until December 2017). In column 4, the approval rate is defined as the number of loans disbursed divided by the number of applications. The interest rate in column 5 is defined as the number of points above above the DTF, the reference rate used by BAC and corresponding to the average rate of fixed term deposits in Colombia. The sample in column 6 includes all municipality-branch combinations with non-zero loan applications at some point between 2009 and 2019. In column 7, month fixed effects are interacted with separate dummies for each of the 16 sets of municipalities with Post-conflict Development Programs, *Programas de Desarrollo con Enfoque Territorial* (PDET). In column 8, the sample period is limited to Juan Manuel Santos' second term as president (Aug 2014 - Jul 2018). The application rate is the monthly number of loan applications at BAC with intended destination to the municipality, normalized by population in 2008 (per 10,000 inhabitants). $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. The sample period in all columns except 3 and 8 is January 2009 to December 2019. All regressions include department-month fixed effects. All columns also include municipality fixed effects, except column 6, which includes municipality-branch and branch-month fixed effects. Baseline controls in all columns include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2008, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Characteristics of Loan Applicants

	Sample: All applicants			Sample: Applicants in scoring models				
	Share New	Share Female	Mean Age	Share w/ Secondary	Mean Assets	Mean Income	Mean Experience	Mean Property Size
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FARC_i x Negotiations_t [a]	-0.005	0.006	0.225					
	(0.009)	(0.005)	(0.138)					
FARC_i x Agreement_t [b]	0.024**	0.010	-0.016	0.017**	-1.351***	-0.017	-2.771	-0.152
	(0.011)	(0.007)	(0.171)	(0.005)	(0.514)	(0.062)	(2.753)	(0.370)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,055	136,055	136,055	82,562	82,562	82,562	82,562	80,373
R-Squared	0.324	0.313	0.289	0.438	0.498	0.531	0.470	0.680
Mean DV	0.376	0.414	44.436	0.388	58.857	3.988	228.520	13.778
p-value H_0: [a] = [b]	0.000	0.418	0.035	-	-	-	-	-

Notes: The unit of observation is the municipality-month. Observations lacking loan applications are excluded from the sample. The sample period in columns 1-4 is January 2009 to December 2019. The sample period in columns 4-8 is July 2012 to February 2019 due to limited data availability from scoring models. The dependent variable is listed in the column header. In column 1, new applicants are defined as not having applied for a loan between January 2005 and the month the application is observed. Applicants' mean assets and annual income in columns 5 and 6 are measured in millions of 2019 COP. In column 7, previous work experience is measured in months. In column 8, mean property size is measured in hectares. FARC_i is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations_t is a dummy for months between June 2011 and October 2016 (both inclusive), which we do not include in columns 4-8 due to lack of data for that period. Agreement_t is a dummy for months on or after November 2016. All regressions include municipality and department-month fixed effects. Baseline controls include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Characteristics of Loans

	Average Loan Size		Share of Disbursed Loans							
	Applied	Disbursed	w/ Own Collateral	Maturity (Years)			Type of Investment (Capital)			Destination Agriculture
				≤ 2	3-5	≥ 6	Fixed	Working	Other	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$FARC_i$ x $Negotiations_t$ [a]	-0.019	-0.056	-0.002	0.009	-0.005	-0.004	-0.018*	0.020**	-0.002	0.001
	(0.122)	(0.120)	(0.012)	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)	(0.002)	(0.011)
$FARC_i$ x $Agreement_t$ [b]	-0.036	-0.080	0.027*	0.004	-0.031**	0.028*	0.003	-0.002	-0.001	-0.016
	(0.151)	(0.149)	(0.014)	(0.016)	(0.014)	(0.016)	(0.013)	(0.014)	(0.004)	(0.013)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	136,055	133,576	133,576	133,576	133,576	133,576	133,576	133,576	133,576	136,055
R-Squared	0.251	0.481	0.636	0.556	0.485	0.562	0.550	0.520	0.738	0.657
Mean DV	8.262	7.863	0.250	0.371	0.368	0.261	0.690	0.271	0.039	0.769
p-value H_0: [a] = [b]	0.881	0.837	0.003	0.626	0.019	0.010	0.010	0.011	0.727	0.052

Notes: The unit of observation is the municipality-month. Observations lacking loan applications (disbursements) are excluded from the sample in columns 1 and 10 (2-9). The dependent variable is listed in the column header. The average amounts requested and disbursed (columns 1-2) are measured in millions of 2019 COP. $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. All regressions include municipality and department-month fixed effects. Baseline controls include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Loan Outcomes

	Average Credit Score	Share of Audits w/ Irregularities	Share of Loans 60 Days Past Due		
			Disbursed		Outstanding
			Year 1	Years 1-2	
	(1)	(2)	(3)	(4)	(5)
FARC$_i$ x Negotiations$_t$ [a]			0.002	0.001	0.003
			(0.002)	(0.004)	(0.005)
FARC$_i$ x Agreement$_t$ [b]	-1.247	0.003	0.001	-0.002	-0.002
	(0.757)	(0.007)	(0.002)	(0.005)	(0.007)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Sample start (MM/YY)	07/12	07/11	01/09	01/09	01/09
Sample end (MM/YY)	02/19	08/18	12/17	12/17	12/19
Observations	82,040	63,767	108,470	108,470	143,881
R-Squared	0.690	0.201	0.225	0.288	0.774
Mean DV	913.857	0.138	0.026	0.083	0.11
p-value H$_0$: [a] = [b]	-	-	0.507	0.351	0.286

Notes: The unit of observation is the municipality-month. The dependent variable in listed in the column header. Observations lacking loan applications in column 1, inspection visits in column 2, disbursed loans in columns 3-4 and outstanding loans in column 5 are excluded from the sample. Credit score in column 1 ranges from 0 to 1,000. In column 2, the outcome is the share of inspection visits in which the officer found any irregularity in the use of the funds. Columns 3-4 calculate the share of disbursed loans per municipality-month that go 60 days past due within the first year (column 3) or the first two years after disbursement (column 4). Column 5 calculates the share of outstanding loans per municipality-month that are 60 days past due. FARC$_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations$_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement$_t$ is a dummy for months on or after November 2016. In columns 1-2, the shorter sample period is due to data availability. In columns 3-4, the sample period is adjusted to ensure we observe all loans for the same number of months. All regressions include municipality and department-month fixed effects. Baseline controls in all columns include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

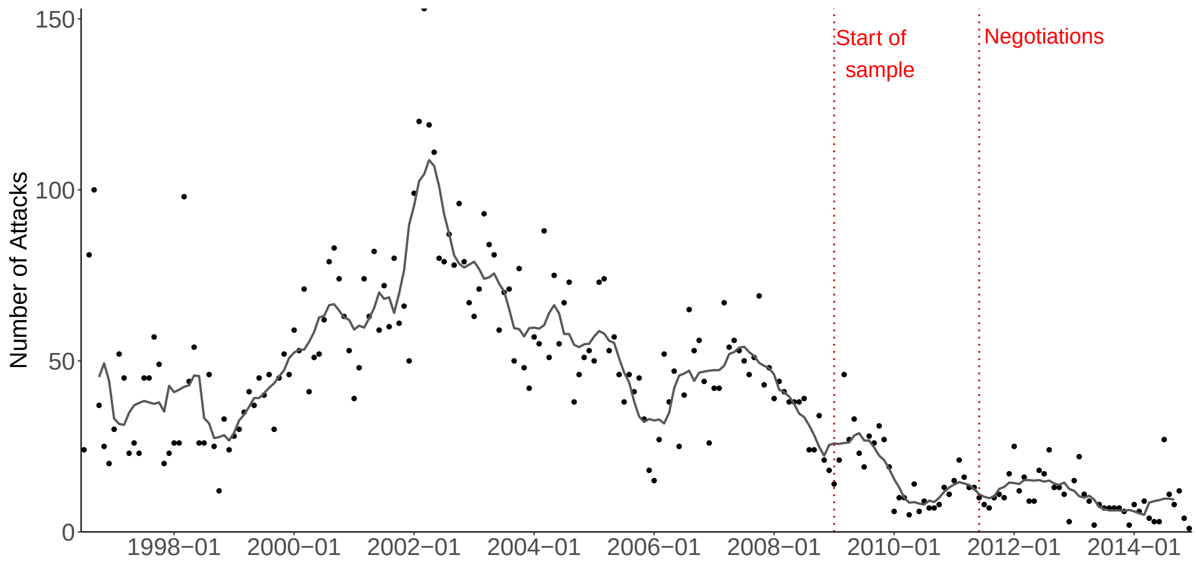
Table 6: Loan Applications: Heterogeneous Effects

Dependent variable: Loan Application Rate

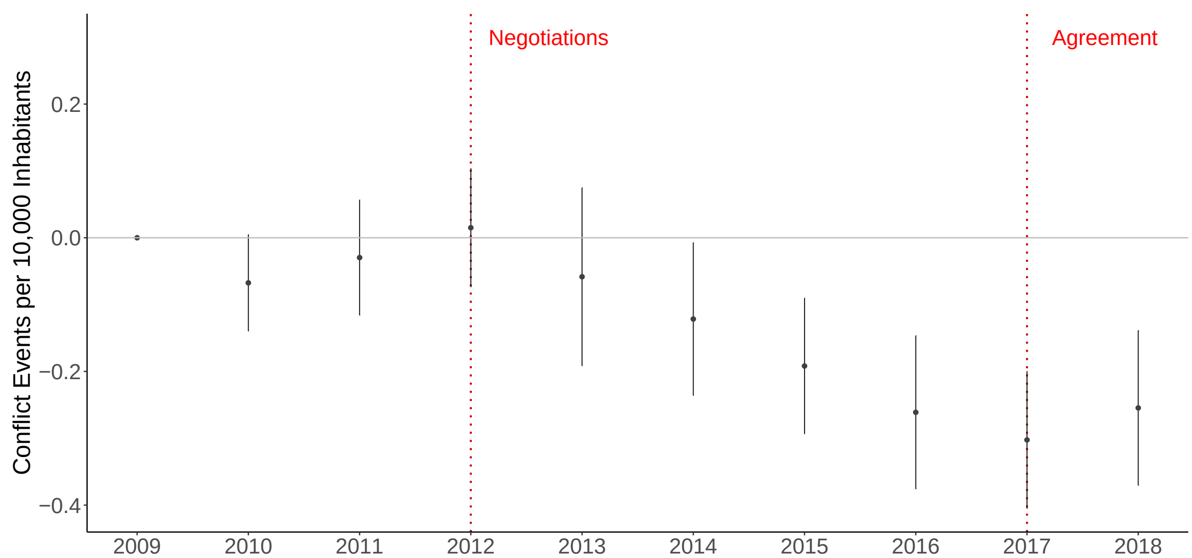
	Source of heterogeneity:					
	Access to			Land Restitution	Formal Land Ownership	Development Index
	Market	Dpt. capital	Bogotá			
	(1)	(2)	(3)	(4)	(5)	(6)
$FARC_i$ x $Negotiations_t$ (Low) [a]	-1.451*	-0.979	-0.320	0.269	0.939	0.488
	(0.780)	(0.812)	(0.803)	(0.839)	(0.764)	(0.773)
$FARC_i$ x $Negotiations_t$ (High) [b]	2.361***	2.093**	1.375	0.946	-0.110	0.643
	(0.906)	(0.860)	(0.944)	(0.820)	(0.984)	(0.915)
$FARC_i$ x $Agreement_t$ (Low) [c]	-0.189	0.698	0.936	1.606	2.613***	1.549*
	(0.831)	(0.844)	(0.850)	(0.986)	(0.952)	(0.816)
$FARC_i$ x $Agreement_t$ (High) [d]	4.530***	3.899***	3.559***	3.203***	1.591	3.040***
	(1.100)	(1.054)	(1.095)	(0.910)	(1.147)	(1.078)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,104	148,104	148,104	148,104	140,448	148,104
R-Squared	0.708	0.708	0.708	0.708	0.712	0.708
Mean DV	17.963	17.963	17.963	17.963	21.354	20.612
p-value H_0: [c] = [d]	0.000	0.008	0.045	0.187	0.443	0.221
p-value H_0: [b] = [d]	0.002	0.01	0.001	0.001	0.022	0.000

Notes: The unit of observation is the municipality-month. In all columns, we divide FARC municipalities into equally-sized groups (i.e. above/below median) based on the variable in the header. We adjust all of these variables, so that high corresponds to a desirable attribute. In columns 1-3, we use access to the wholesale market, to the departmental capital and to Bogotá based on distance in kilometers. In column 4, we use total applications for land restitution per municipality since 2011 (per 10,000 inh. in 2008). In column 5, we use an index for formal land ownership in the municipality, averaged over 2000-2008. In column 6, we use the share of the population not considered to be poor according to the index of Unmet Basic Needs (UBN) in the 2005 census. $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. All regressions include municipality and department-month fixed effects. Baseline controls in all columns include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1: Conflict Intensity



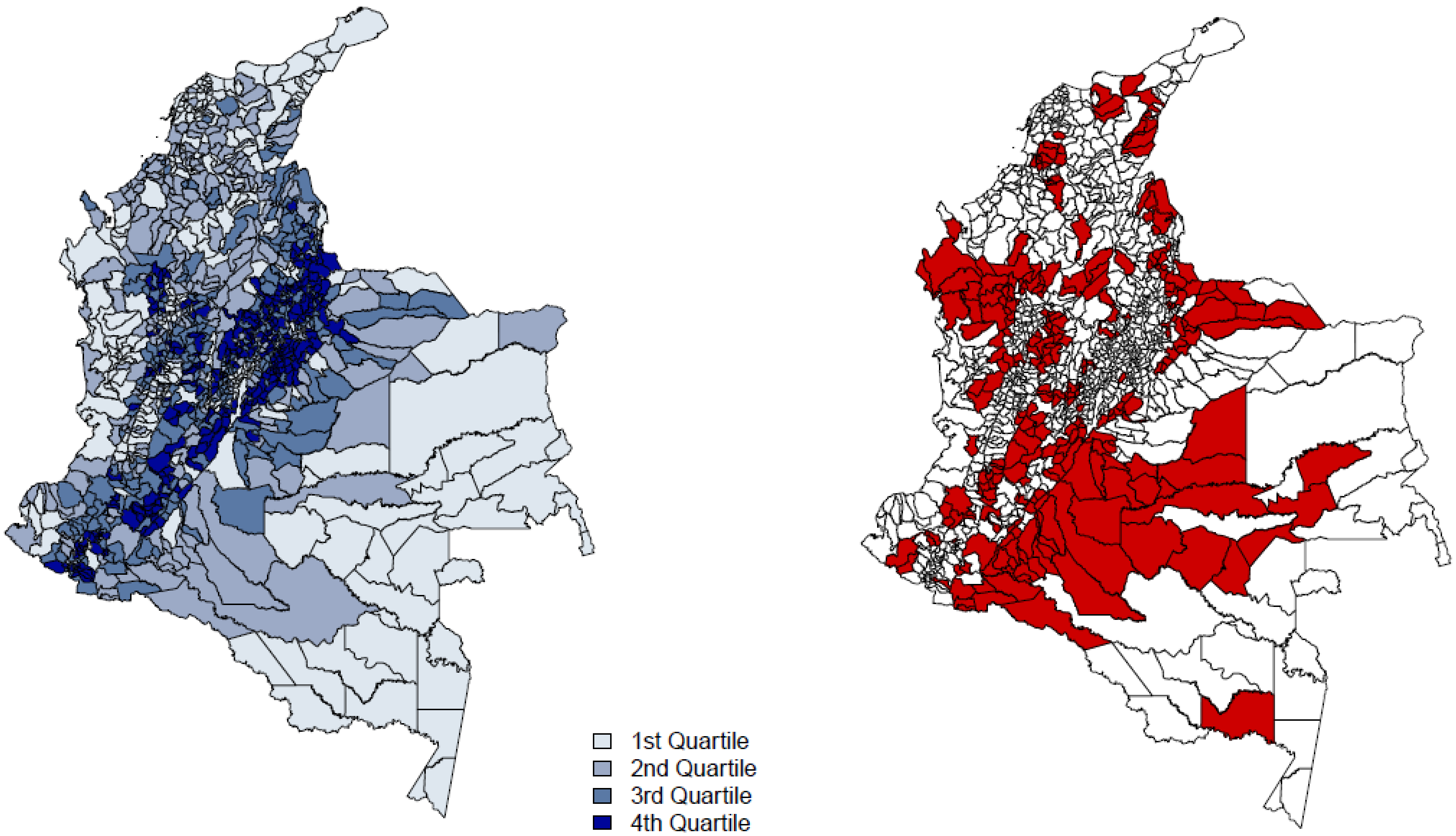
(a) Monthly FARC Events (1996-2014)



(b) Conflict Intensity: Event study (2009-2018)

Notes: Panel (a) shows the monthly number of conflict events involving FARC between January 1996 and December 2014. Panel (b) shows point estimates and 95% confidence intervals from a regression of a standardized family of outcomes related to conflict intensity on yearly dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the municipality-year. The regression includes municipality and department-year fixed effects, as well as sets of year fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors clustered two-way by municipality and department-year.

Figure 2: FARC Exposure and Total Loan Applications

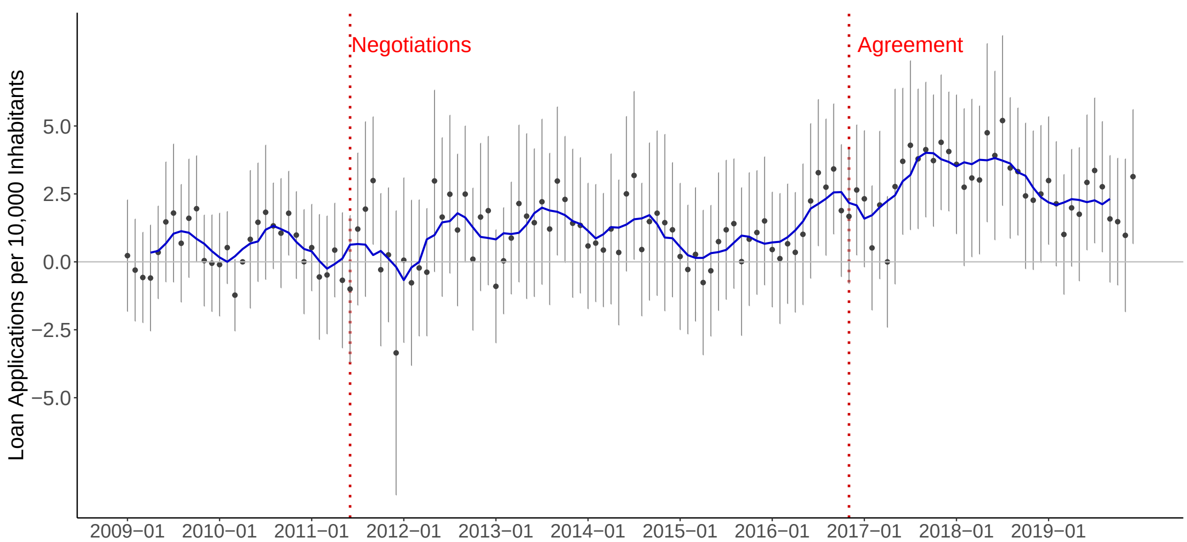


(a) Loan Applications per 10,000 inh. (2009-2019)

(b) FARC Exposure (1996-2008)

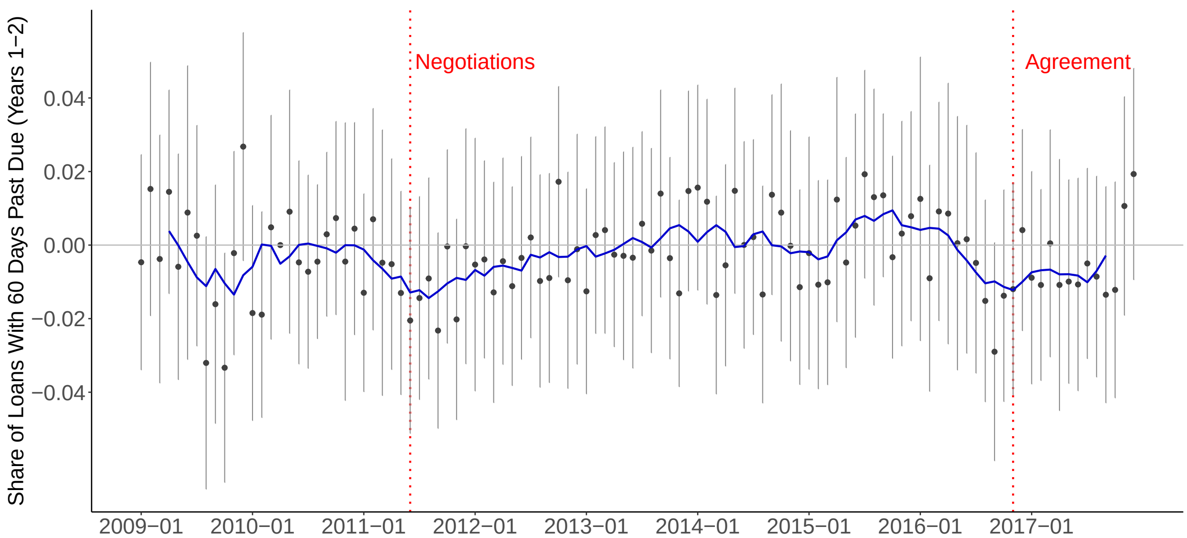
Notes: Panel (a) shows quartiles of the distribution of total loan applications to BAC per 10,000 inhabitants in the period 2009-2019. Panel (b) shows the municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008.

Figure 3: Loan Applications: Event Study



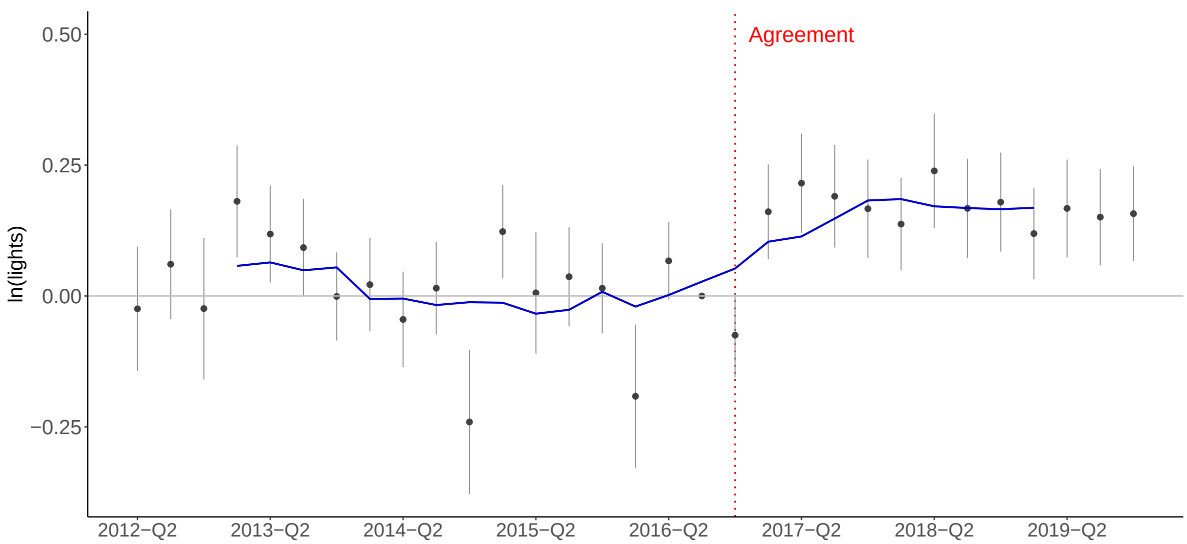
Notes: This figure shows point estimates and 95% confidence intervals from a regression of the monthly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality on monthly dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the municipality-month. Regression includes municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. The solid line depicts a moving average of the three previous and the three following point estimates. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure 4: Loan Defaults: Event study



Notes: This figure shows point estimates and 95% confidence intervals from a regression of the share of loans issued in a municipality-month that are in default for 60 days or more during their first two years. The sample only includes loans in their first two years and the sample period finishes in December 2017, though we track loans until December 2019. Markers correspond to point estimates for monthly dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the municipality-month. The regression includes municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. The solid line depicts a moving average of the three previous and the three following point estimates. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure 5: Nighttime Luminosity: Event study

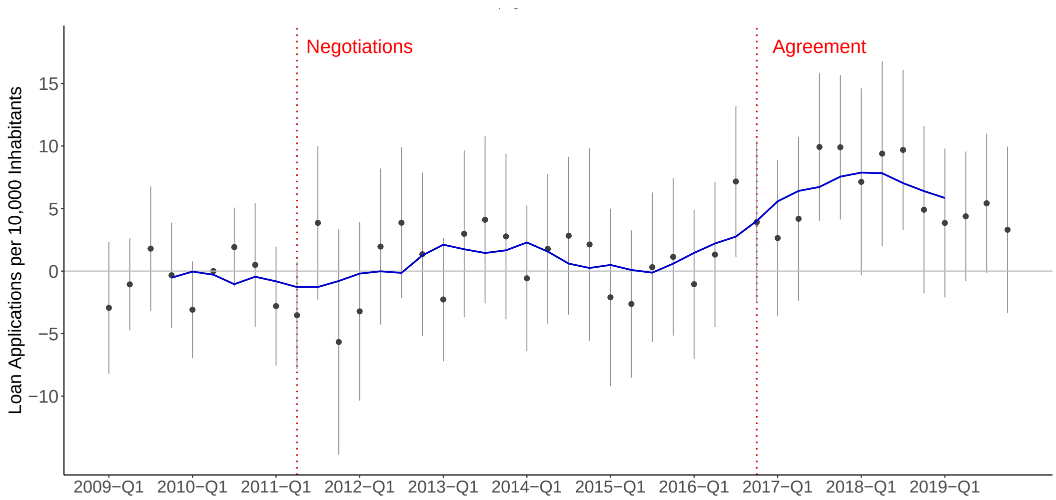


Notes: This figure shows point estimates and 95% confidence intervals from a regression of the log of nighttime luminosity at the municipality-quarter level. Markers correspond to point estimates for quarterly dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The monthly nighttime lights values, are averaged by quarter, from the VIIRS dataset. The regression includes municipality and department-quarter fixed effects, as well as additional sets of quarter fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. The solid line depicts a moving average of the three previous and the three following point estimates. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

APPENDIX (for online publication)

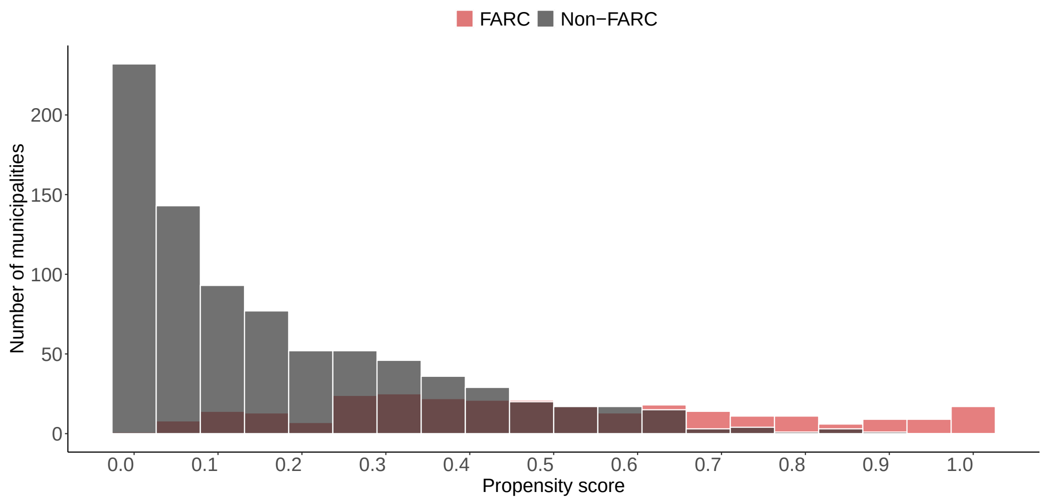
Appendix A Additional Figures and Tables

Figure A1: Loan Applications: Event study (municipality-quarter level)



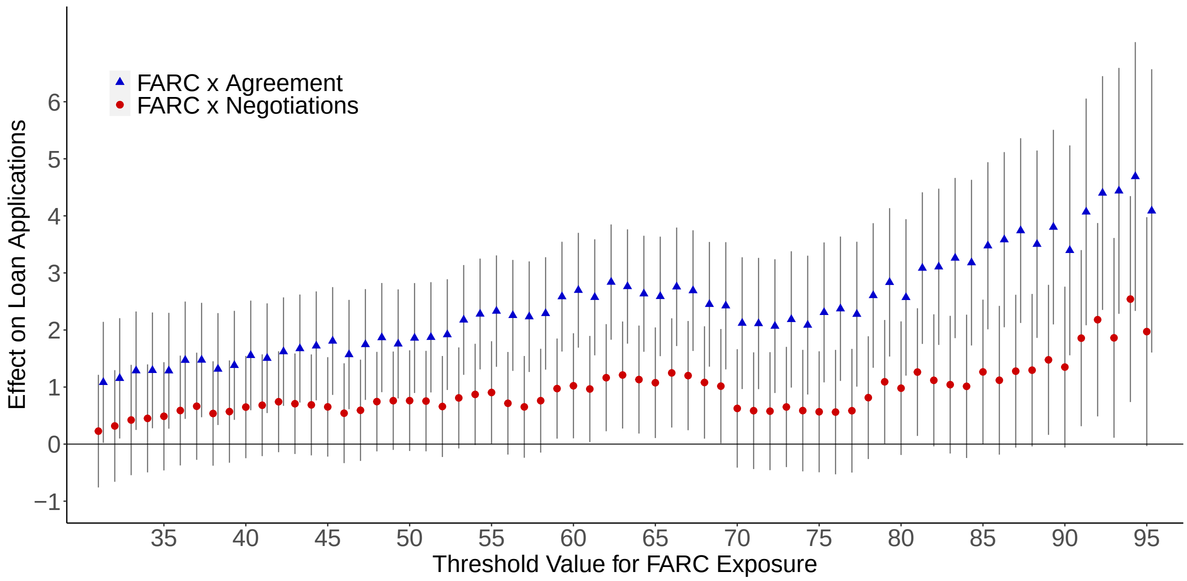
Notes: This figure shows point estimates and 95% confidence intervals from a regression of the quarterly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality on quarter dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the municipality-quarter. The regression includes municipality and department-quarter fixed effects, as well as additional sets of quarter fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. The solid line depicts a moving average of the three previous and the three following point estimates. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A2: Distribution of Propensity Scores for FARC Exposure



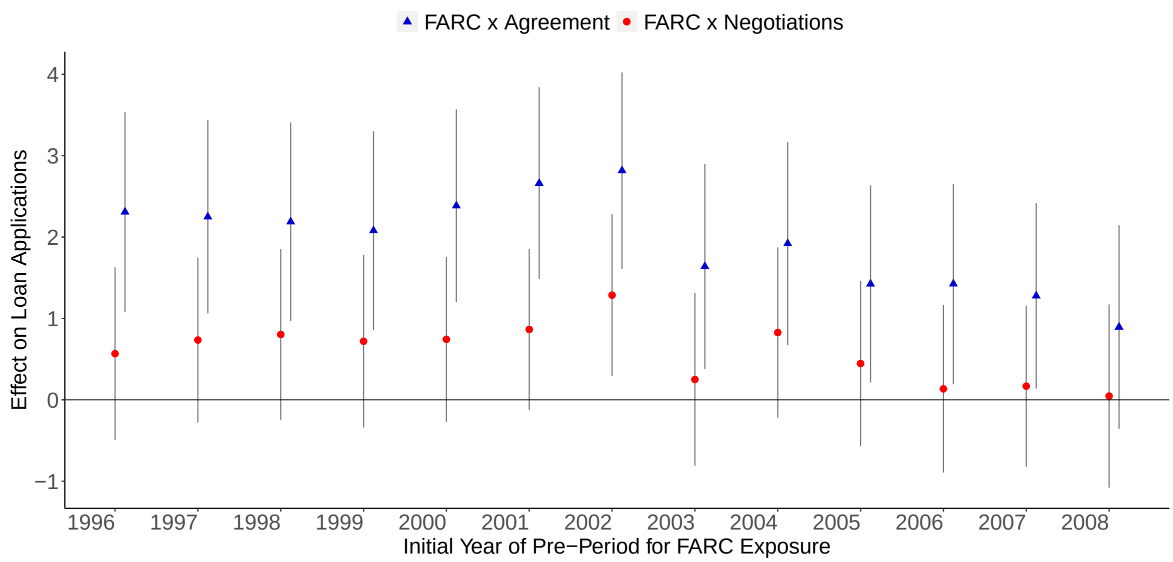
Notes: This figure shows the distribution of propensity scores for FARC exposure, disaggregated by actual exposure. FARC exposure takes a value of one for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. The propensity scores are fitted values from a Probit regression of FARC exposure on 23 pre-determined municipal characteristics and department fixed effects. The common support ranges from 0.05 to 0.75 (757 municipalities).

Figure A3: Loan Applications: Different threshold for FARC exposure



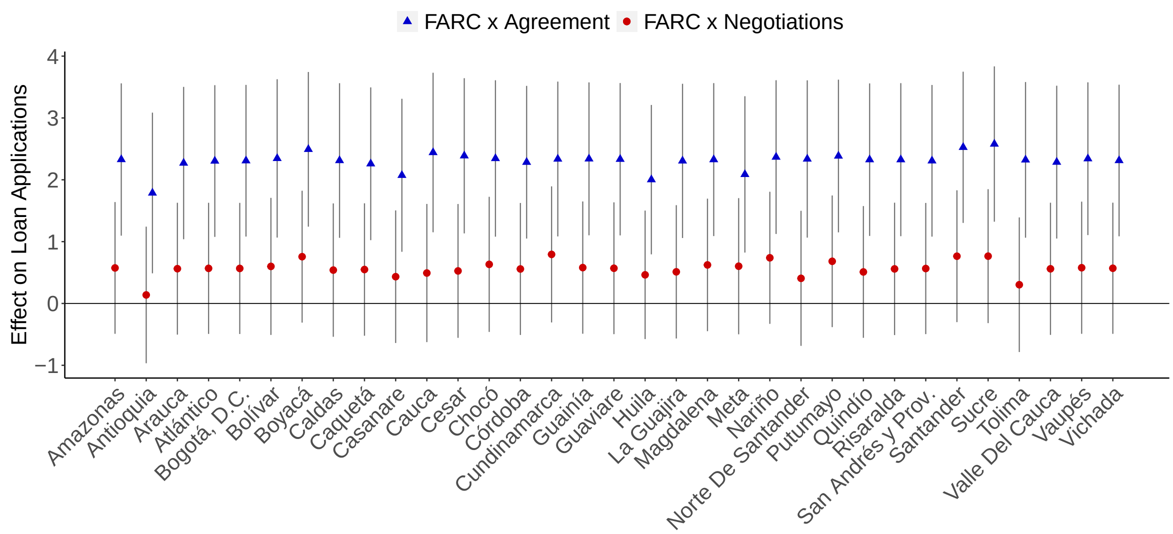
Notes: This figure shows point estimates and 95% confidence intervals from separate regressions of the monthly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality on the interaction of a dummy for FARC exposure with separates dummies for the negotiations and agreement periods (i.e. our main specification). FARC exposure takes a value of one for municipalities above the percentile in the x-axis of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008 (baseline = 75). Negotiations$_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement$_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. The unit of observation is the municipality-month. All regressions include municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A4: Loan Applications: Treatment defined with different time periods of FARC attacks



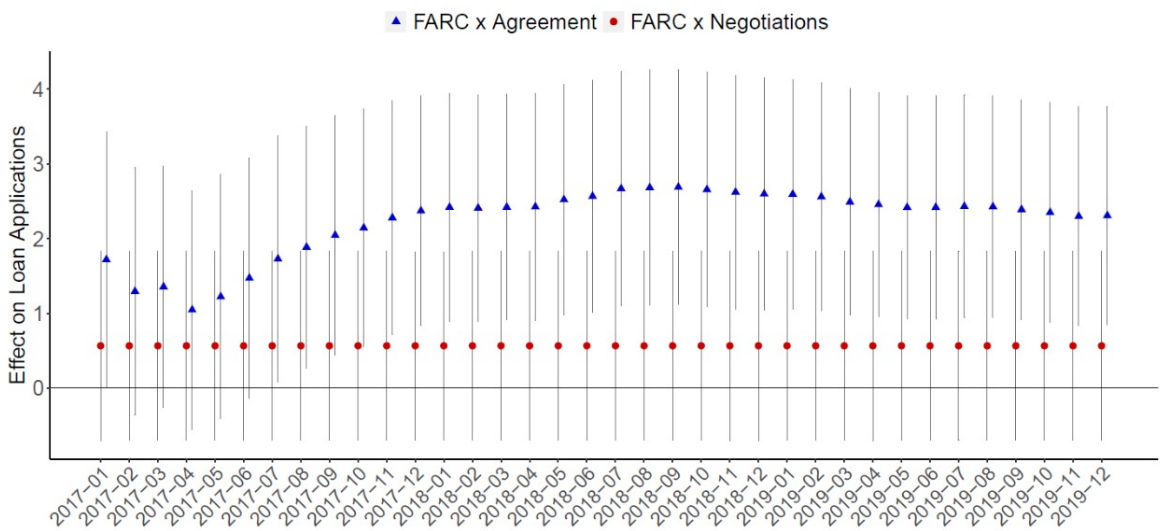
Notes: This figure shows point estimates and 95% confidence intervals from separate regressions of the monthly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality on the interaction of a dummy for FARC exposure with separates dummies for the negotiations and agreement periods (i.e. our main specification). FARC exposure takes a value of one for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between the year in the x-axis and 2008. Negotiations$_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement$_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. The unit of observation is the municipality-month. All regressions include municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A5: Loan Applications: Removing one department



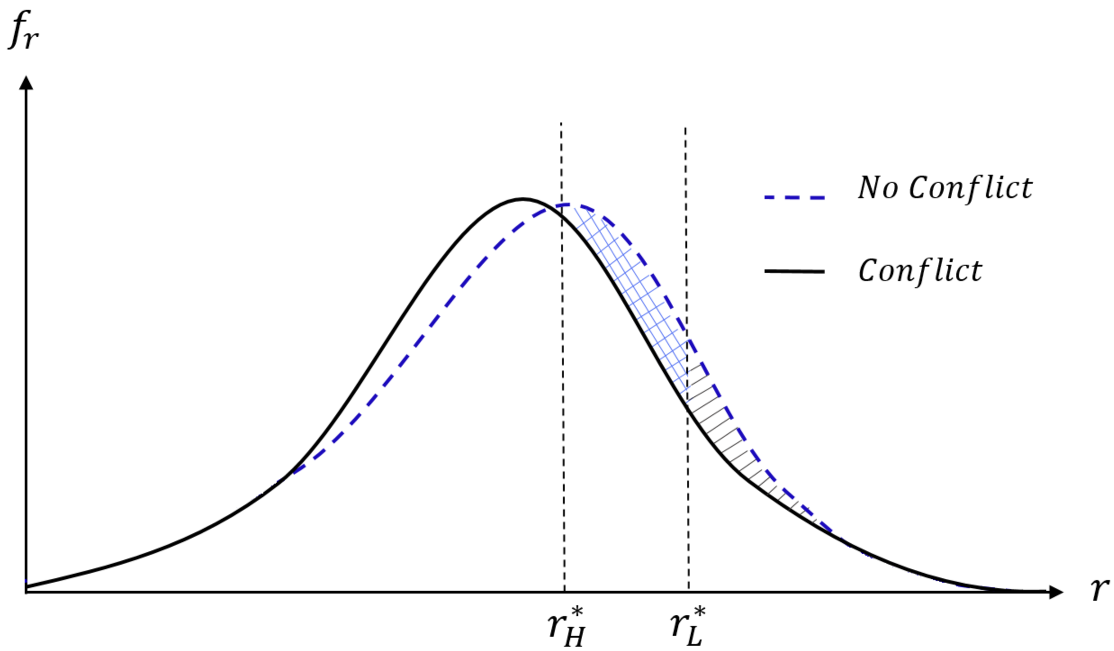
Notes: This figure shows point estimates and 95% confidence intervals from separate regressions excluding the department in the x-axis from the sample. The dependent variable is the monthly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality. The regressors of interest are the interaction of a dummy for FARC exposure with separates dummies for the negotiations and agreement periods (i.e. our main specification). FARC exposure takes a value of one for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations$_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement$_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. The unit of observation is the municipality-month. All regressions include municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A6: Loan Applications: Changes to Sample End Date



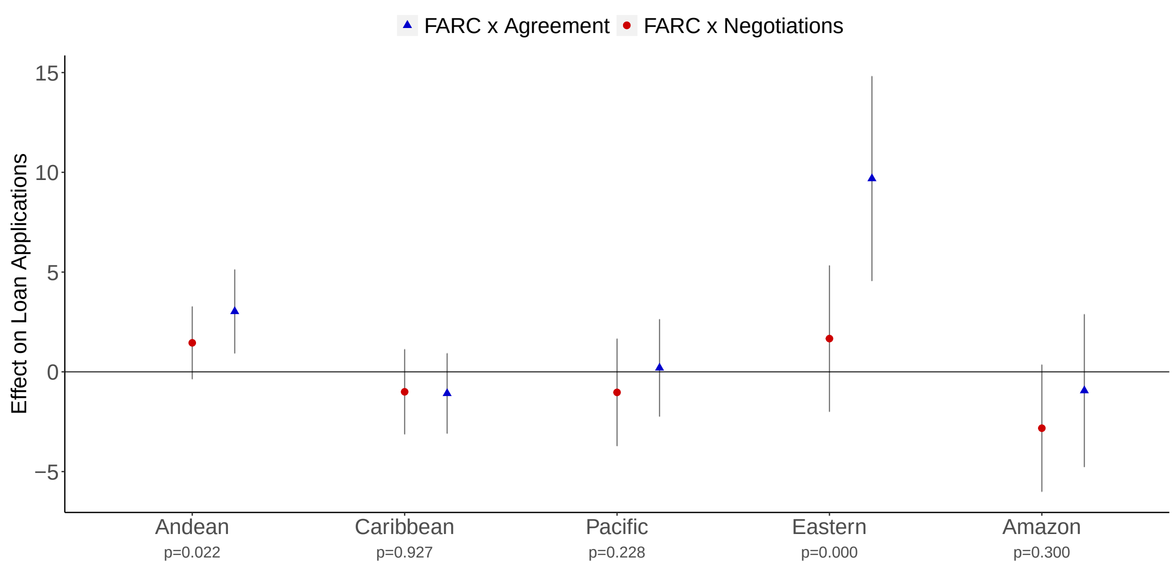
Notes: This figure shows point estimates and 95% confidence intervals from separate regressions in which the final month in the sample is indicated in the x-axis. The dependent variables is the monthly number of loan applications (per 10,000 inhabitants) with intended destination to the municipality. The regressors of interest are the interaction of a dummy for FARC exposure with separates dummies for the negotiations and agreement periods (i.e. our main specification). FARC exposure takes a value of one for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations_t is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement_t is a dummy for months on or after November 2016. The sample period starts in January 2009. The unit of observation is the municipality-month. All regressions include municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A7: Heterogeneous Effects of the End of Conflict



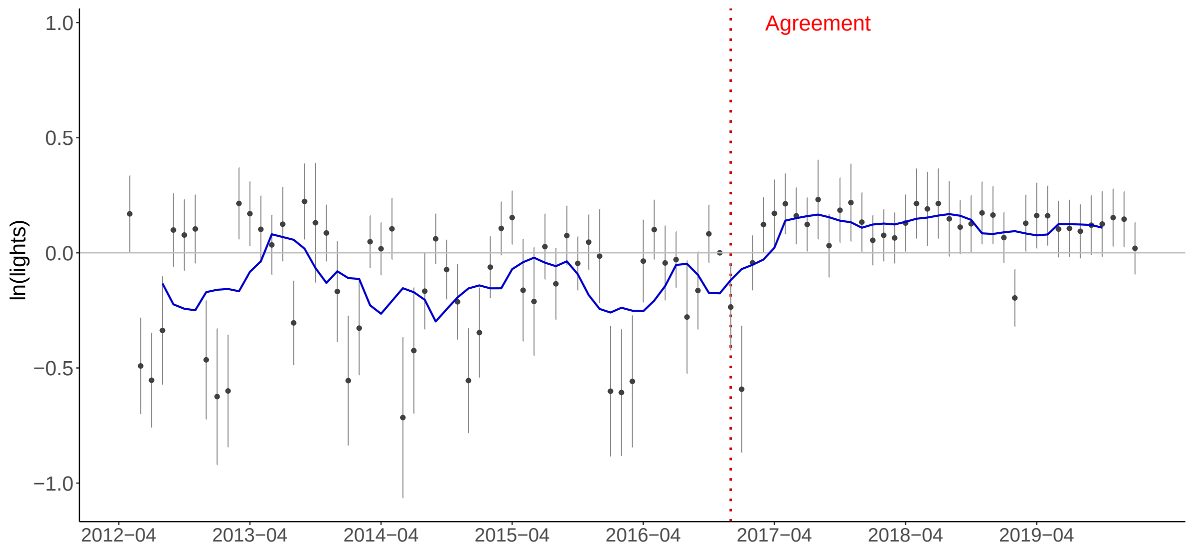
Notes: This diagram explains how our stylized model of investment can incorporate heterogeneous effects of the peace agreement based on access to markets. The graph shows two Probability Density Functions (PDFs) of the return to investment, r. The black curve corresponds to the PDF with conflict, while the blue curve corresponds to the PDF without conflict. We assume that conflict decreases the return to investment (i.e., shifts the PDF to the left). Based on our model, we assume that farmers pursue investment opportunities with a return exceeding a threshold value, $r^\star$, which depends on other parameters. In particular, heterogeneity across municipalities in access to markets affects the cost of investment (c) and leads to differential thresholds. Municipalities with High access to markets have a threshold $r_H^\star$, while those with Low access to markets have a threshold $r_L^\star$, where $r_L^\star > r_H^\star$ since $c_L > c_H$. The shaded area indicates the increase in investment (and in demand for credit) resulting from the end of conflict. For municipalities with low access to markets, the gain in investment is small (the area depicted with dark lines) since the indifference threshold is very high, while for municipalities with high access to markets the increase in investment is much larger (represented by the area with dark lines *and* the area with blue crossing lines).

Figure A8: Heterogeneous Effects: Geographical Regions



Notes: This figure shows point estimates and 95% confidence intervals from a regression of loan applications at the municipality-month level, normalized by 2008 population. Municipalities are classified according to their geographical region. The regressors of interest are the interaction of a dummy for FARC exposure with separate dummies for the negotiations and agreement periods and separate dummies for each geographical region. The p-value shown in the x-axis corresponds to the null hypothesis of equal means during the negotiation and agreement periods for each region. The unit of observation is municipality-month. The regression includes municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Figure A9: Nighttime Luminosity: Event study (municipality-month level)



Notes: This figure shows point estimates and 95% confidence intervals from a regression of the log of nighttime luminosity at the municipality-month level. Markers correspond to point estimates for monthly dummies interacted with an indicator for municipalities with FARC exposure (i.e. in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the municipality-month. The source of the nighttime lights data is the VIIRS. The regression includes municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with time-invariant measures of (i) rural share of population, (ii) the basket of crops produced in the municipality, (iii) coca cultivation. The solid line depicts a moving average of the three previous and the three following point estimates. See the text for further details. Standard errors are clustered two-way by municipality and department-year.

Table A1: Summary Statistics

	Mean	Median	St. Dev.	Obs
Panel A. Characteristics of Loan Applications				
Applications per 10,000 inhabitants	17.963	12.169	19.189	148104
Approval rate	0.778	0.814	0.193	136055
Share agricultural	0.712	0.805	0.299	136055
Average size	8.262	7.891	4.801	136055
Share in scoring models	0.832	0.929	0.237	84372
Share with credit score	0.870	0.909	0.156	82562
Average credit score	913.857	918.556	43.809	82040
Share in the field	0.323	0.208	0.340	110648
Panel B. Characteristics of Disbursed Loans				
Loans disbursed per 10,000 inhabitants	14.382	9.331	15.967	148104
Average amount disbursed	7.863	7.495	3.305	133576
Total amount disbursed per 10,000 inhabitants	114.661	67.018	141.532	148104
Average interest rate	11.807	7.598	8.366	133576
Share government collateral	0.751	0.889	0.302	133576
Share own assets as collateral	0.250	0.115	0.302	133576
Share maturity $\leq$ 2 years	0.371	0.333	0.301	133576
Share maturity 3-5 years	0.368	0.333	0.287	133576
Share maturity $\geq$ 5 years	0.261	0.167	0.286	133576
Panel C. Loan Outcomes				
Share 60 days overdue (year 1)	0.026	0.000	0.074	108470
Share 120 days overdue (year 1)	0.015	0.000	0.054	108470
Share 60 days overdue (years 1-2)	0.083	0.037	0.136	108470
Share 120 days overdue (years 1-2)	0.062	0.000	0.118	108470
Share with inspection visits	0.223	0.133	0.258	88931
Share of visits with any irregularity	0.138	0.000	0.243	63767
Panel D. Applicant Characteristics				
Share women applicants	0.414	0.416	0.212	136055
Average applicant age	44.436	44.073	5.433	136055
Share new clients	0.376	0.354	0.231	136055
Share with secondary education	0.338	0.323	0.218	82562
Share with tertiary education	0.050	0.000	0.098	82562
Previous experience	228.520	224.870	84.028	82562
Average assets	58.857	58.386	14.433	82562
Average yearly income	3.988	3.325	2.189	82562
Average farm area	13.778	7.117	20.100	80373

Notes: The unit of observation is the municipality-month. In Panel A, applications per 10,000 inhabitants refers to the number of loan applications with intended destination to the municipality, normalized by population in 2008. The approval rate is defined as the number of loans disbursed divided by applications. Agricultural loans exclude those intended for other small businesses. Average loan size is measured in millions of 2019 COP. Applications with credit score refer to those with credit history. Share in the field refers to applications arising from field visits by BAC representatives to farmers. In Panel B, average amount disbursed and total amount disbursed are measured in millions of 2019 COP. The average interest rate is defined with the number of points above the DTF, the reference rate used by BAC and corresponding to the average rate of fixed term deposits in Colombia. Government collateral comes from state guaranty funds. Panel C shows the share of disbursed loans that entered into periods of 60 or 120 days past due within the first year after disbursement or the first two years after disbursement. Loans with inspection visits had an in-person inspection visit from a BAC officer. Visits with any irregularity are those in which the officer found any discrepancy in the use of the funds. In Panel D, new clients are defined as having never applied for a loan at BAC between 2005 and the month of the application. Share with secondary or tertiary education is defined as the percentage of clients whose highest degree of education is secondary or tertiary, respectively. Previous experience in productive activities is measured in months. Applicant's average assets and yearly income are measured in millions from 2019 COP. Average farm area is measured in hectares.

Table A2: Municipal Characteristics and FARC Exposure

	Sub-sample Average		P-value	Probit	LASSO	Municipalities
	Non-FARC	FARC	(1) = (2)	Coefficients	Variables	with data
	(1)	(2)	(3)	(4)	(5)	(6)
Population (x 1,000)	47.439	16.208	0.001	-0.010***	0	1122
Altitude (meters)	1148.369	1116.872	0.761	0.0002**	0	1122
Area (hectares)	88.052	142.785	0.007	-0.0001	0	1122
𝟙(Departmental capital)	0.037	0.007	0.000	-0.612	0	1122
Rural share of population	0.560	0.638	0.000	0.5	1	1122
𝟙(BAC branch)	0.600	0.730	0.000	0.372**	1	1122
Distance to nearest BAC branch (Km)	9.227	8.046	0.458	0.001	0	1122
Distance to departmental capital (Km)	80.712	83.690	0.431	-0.001	0	1122
Distance to nearest market (Km)	131.839	124.394	0.262	-0.005***	0	1122
Distance to Bogotá (Km)	324.964	311.342	0.250	0.003***	0	1122
Literacy rate	84.570	81.726	0.000	-0.017*	0	1122
Infant mortality rate	22.999	25.948	0.000	0.006	0	1122
Coffee cultivation (share of area)	0.007	0.006	0.051	-5.98	0	1122
Corn cultivation (share of area)	0.004	0.002	0.000	-16.387	1	1122
Rice cultivation (share of area)	0.002	0.001	0.009	-27.090**	0	1122
Sugar cane cultivation (share of area)	0.005	0.002	0.001	-5.661	1	1122
Banana cultivation (share of area)	0.003	0.002	0.000	-56.000***	1	1122
Oil palm cultivation (share of area)	0.001	0.000	0.011	-37.175*	0	1122
Yucca cultivation (share of area)	0.001	0.001	0.011	-21.261	0	1122
Potato cultivation (share of area)	0.003	0.000	0.000	-106.154***	1	1122
Cacao cultivation (share of area)	0.000	0.001	0.379	9.781	0	1122
Beans cultivation (share of area)	0.001	0.001	0.160	-0.795	0	1122
Coca cultivation (share of area)	0.000	0.001	0.000	150.828***	1	1122
𝟙(Andean Region)	0.566	0.544	0.531	-	-	1122
𝟙(Caribbean Region)	0.200	0.103	0.000	-	-	1122
𝟙(Pacific Region)	0.166	0.135	0.196	-	-	1122
𝟙(Eastern Region)	0.036	0.103	0.001	-	-	1122
𝟙(Amazon Region)	0.032	0.114	0.000	-	-	1122
Unmeet basic needs index	42.805	51.276	0.000	N/A	N/A	1114
Multidimensional poverty index	67.712	74.647	0.000	N/A	N/A	1113
Land informality	0.181	0.280	0.000	N/A	N/A	948
GINI index	0.718	0.681	0.000	N/A	N/A	957
GDP per capita	7.190	6.467	0.028	N/A	N/A	1053
Municipal spending per capita	0.261	0.238	0.000	N/A	N/A	1043
Municipal revenue per capita	0.436	0.482	0.033	N/A	N/A	1100
Municipal transfers per capita	0.045	0.057	0.001	N/A	N/A	1100
Fiscal performance index	58.051	56.097	0.000	N/A	N/A	1100
Municipal development index	44.607	39.371	0.000	N/A	N/A	1097
Share of 5-24 yo in school	62.112	57.534	0.000	N/A	N/A	1030
Average years of education	7.259	6.614	0.000	N/A	N/A	1113
Aqueduct coverage	60.887	55.641	0.035	N/A	N/A	1020
Sanitation coverage	45.717	45.926	0.931	N/A	N/A	1020
Sewerage coverage	42.092	43.167	0.657	N/A	N/A	1020
Share underweight births	0.070	0.062	0.000	N/A	N/A	1121
Share with subsidized health	0.554	0.627	0.000	N/A	N/A	1098

Notes: The unit of observation is the municipality. Population and rural share of population are from year 2008. The measures of BAC presence are from 2008. The literacy index is taken from the 2005 census. Child mortality rate is averaged between 2000 and 2008. The share of municipal land dedicated to the cultivation of each crop is averaged between 2000 and 2008. The geographical distribution of municipalities corresponds to the five main regions of Colombia. Unmeet basic needs and multidimensional poverty are taken from the 2005 census. Land informality and GINI index are averaged between 2000 and 2008. GDP per capita, municipal spending, municipal income, municipal transfers, fiscal performance index and municipal development index are also averaged between 2000 and 2008. The share of population attending educational institutions is calculated among people aged between 5 and 24 years. Average years of education are calculated for inhabitants older than 15 years. Both measures are taken from the 2005 census. Public services coverage (aqueduct, sanitation and sewerage) are measured in 2008. The share of underweight births and the share of the population with subsidized health are also measured in 2008. In columns 1-2, FARC municipalities are those in the upper quartile of the distribution of FARC attacks. The p-value in column 3 corresponds to the null hypothesis of equal means in FARC and non-FARC municipalities. Column 4 shows the coefficients from the Probit regression used to calculate the propensity scores of each municipality, while column 5 shows the optimal controls selected by LASSO. In columns 4-5, only variables without any missing values were included in the regression. Department fixed effects are included in the Probit and LASSO regressions. Column 6 shows the number of municipalities with available data for each variable. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A3: Conflict Intensity (2009-2018)

	Variables per 10,000 Inhabitants												
	Family of Outcomes	Land Theft	Terrorism	Threats	Sexual Violence	Forced Disappearance	Forced Displacement	Homicide	Land Mines	Property Loss	Kidnapping	Torture	Underage Recruitment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
FARC_i x Negotiations_t [a]	-0.097***	-0.018	0.801	5.632***	0.018	-0.163	-20.507*	-2.111***	-0.870***	-1.710	-0.084*	-0.028	-0.031
(2012-2016)	(0.033)	(0.017)	(0.644)	(1.312)	(0.046)	(0.139)	(12.309)	(0.535)	(0.191)	(1.041)	(0.044)	(0.042)	(0.042)
FARC_i x Agreement_t [b]	-0.202***	-0.014	-0.479	0.395	0.0003	-0.351***	-35.945*	-3.210***	-1.042***	-1.988*	-0.182***	-0.091	-0.102***
(2017-2018)	(0.045)	(0.016)	(0.471)	(1.585)	(0.119)	(0.113)	(19.294)	(0.585)	(0.202)	(1.081)	(0.065)	(0.076)	(0.037)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220	11,220
R-Squared	0.656	0.228	0.374	0.678	0.386	0.277	0.541	0.550	0.396	0.429	0.401	0.436	0.379
Mean DV	0	0.012	1.371	9.772	0.223	0.262	75.727	2.236	0.246	2.151	0.153	0.046	0.078
p-value H_0: [a] = [b]	0.001	0.517	0.104	0.002	0.877	0.039	0.349	0.000	0.005	0.727	0.044	0.123	0.035

Notes: The unit of observation is the municipality-year. The dependent variables are taken from the Colombian Registry of Victims. In column 1, the family of outcomes is constructed as the average of the standarized variables in columns 2-13. The outcome in columns 2-13 refers to the number of victims (per 10,000 inhabitants) affected by each type of event. FARC_i is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations_t is a dummy for years between 2012 and 2016 (both inclusive). Agreement_t is a dummy for the years 2017 and 2018. Sample period: 2009-2018. All regressions include municipality and department-year fixed effects. Additional controls include: (i) interactions of dummies for quartiles of the distribution of rural share of population in 2005 with year fixed effects; (ii) year fixed effects interacted with dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008; (iii) year fixed effects interacted with a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Loan Applications: Additional variables in LASSO and Propensity Score

	Dependent variable: Loan Application rate			
	LASSO		Propensity Score	
	Few missings	All	Few missings	All
	(1)	(2)	(3)	(4)
FARC_i x Negotiations_t [a]	0.190	0.227	0.555	0.800
	(0.660)	(0.666)	(0.914)	(1.064)
FARC_i x Agreement_t [b]	1.922**	2.163***	2.067**	2.159*
	(0.773)	(0.798)	(0.980)	(1.160)
Municipality FE	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes
LASSO controls	Yes	Yes	No	No
Propensity score weights	No	No	Yes	Yes
First-stage variables	37	45	37	45
Observations	144,804	144,804	90,024	57,156
R-squared	0.699	0.697	0.686	0.690
Mean DV	18.356	18.356	20.236	23.595
p-value H_0: [a] = [b]	0.001	0.001	0.006	0.064

Notes: The unit of observation is the municipality-month. The dependent variable is the monthly number of loan applications at BAC with intended destination to the municipality, normalized by population in 2008 (per 10,000 inhabitants). FARC_i is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Negotiations_t is a dummy for months between June 2011 and October 2016 (both inclusive). Agreement_t is a dummy for months on or after November 2016. Sample period: January 2009-December 2019. All regressions include municipality and department-month fixed effects. Columns 1-2 include month fixed effects interacted with predetermined controls selected using a LASSO procedure. Columns 3-4 restrict the sample to municipalities in the common support for predicted FARC presence and weight non-FARC observations by a function of their estimated propensity score. In columns 1 and 3, 37 municipality characteristics with few missing values are included in the first stage for the LASSO or the propensity score estimation. In columns 2 and 4, all 45 available variables are included in the first stage estimation. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Loan Applications: Additional Robustness Checks

	Dependent variable: Loan Application rate					
	Δ Negotiation Start Date	Quarter-level Aggregation	Size Controls		FARC Exposure	
			Population	Category	Continuous	CEDE
	(1)	(2)	(3)	(4)	(5)	(6)
FARC_i x Negotiations_t [a]	0.680	1.418	0.408	0.461	0.075**	1.351**
	(0.562)	(1.929)	(0.684)	(0.656)	(0.038)	(0.651)
FARC_i x Agreement_t [b]	2.278***	6.718***	2.170***	2.238***	0.164***	3.551***
	(0.649)	(2.250)	(0.765)	(0.757)	(0.041)	(0.732)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Population quartile x Month FE	No	No	Yes	No	No	No
Municipal category x Month FE	No	No	No	Yes	No	No
Observations	148,104	49,368	148,104	144,936	148,104	145,068
R-squared	0.707	0.799	0.709	0.703	0.708	0.704
Mean DV	17.963	53.890	17.963	18.342	17.963	18.306
p-value H_0: [a] = [b]	0.001	0.000	0.000	0.000	0.002	0.000

Notes: The unit of observation is the municipality-month except in column 2, where it is municipality-quarter. The dependent variable is the monthly (quarterly in column 2) number of loan applications at BAC with intended destination to the municipality, normalized by population in 2008 (per 10,000 inhabitants). FARC_i is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008, except in column 5 where we use the continuous measure of FARC events per 10,000 inhabitants. The source of data on FARC activity is Universidad del Rosario, except in column 6 where we use data from CEDE at Universidad de los Andes. Negotiations_t is a dummy for months between June 2011 and October 2016 (both inclusive), except in column 1, where we set the start date for the negotiations phase to September 2012. Agreement_t is a dummy for months on or after November 2016. Sample period: January 2009-December 2019. All regressions include municipality and department-month fixed effects. Baseline controls in all columns include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Column 3 additionally includes month fixed effects interacted with dummies for quartiles of the distribution of total population in 2008, while column 4 includes month fixed effects interacted with dummies for the municipal categories in 2008. Standard errors clustered two-way by municipality and department-year reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Additional Loan Characteristics

	Applications in Scoring Models			Share w/ Inspection Visits
	Share in Models	Per 10,000 inhabitants	Share w/ Credit Score	
	(1)	(2)	(3)	(4)
$FARC_i$ x $Agreement_t$	0.015*	1.826***	-0.002	0.019*
	(0.008)	(0.498)	(0.005)	(0.011)
Municipality FE	Yes	Yes	Yes	Yes
Department x Time FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Observations	84,372	89,760	82,562	88,931
R-Squared	0.605	0.768	0.390	0.488
Mean DV	0.832	19.409	0.87	0.223

Notes: The unit of observation is the municipality-month. In columns 1-3, data comes from scoring models and is only available for loan applications between July 2012 and February 2019. Column 1 refers to the share of applications that went through scoring models. Column 2 refers to the number of applications that went through scoring models, normalized by the municipality's population in 2008. In column 3, the share of applications without a credit bureau score corresponds to those without credit history. In column 4, the outcome is the share of disbursed loans that had an in-person inspection visit from a BAC offcer. Data on inspection visits is available between July 2011 and August 2018. $Agreement_t$ is a dummy for months on or after November 2016. All regressions include municipality and department-month fixed effects. Baseline controls in all columns include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Other Loan Outcomes

	Share of Disbursed Loans						
	30 Days Past Due		120 Days Past Due		Outstanding		Extended
	Year 1	Years 1-2	Year 1	Years 1-2	30 Days	120 Days	Payments
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$FARC_i$ x $Negotiations_t$ [a]	0.004*	0.005	0.002	0.0001	0.004	0.003	0.001
	(0.002)	(0.004)	(0.001)	(0.003)	(0.005)	(0.005)	(0.007)
$FARC_i$ x $Agreement_t$ [b]	0.003	0.003	0.0002	-0.004	-0.002	-0.003	0.008
	(0.003)	(0.006)	(0.002)	(0.004)	(0.007)	(0.006)	(0.009)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Start (MM/YY)	01/09	01/09	01/09	01/09	01/09	01/09	01/09
Sample end (MM/YY)	12/17	12/17	12/17	12/17	12/19	12/19	12/10
Maturity of Loans	Any	Any	Any	Any	Any	Any	$\leq$ 2 Years
Observations	108,470	108,470	108,470	108,470	143,881	143,881	83,021
R-Squared	0.249	0.295	0.182	0.271	0.777	0.771	0.248
Mean DV	0.04	0.112	0.015	0.062	0.12	0.1	0.143
p-value H_0: [a] = [b]	0.774	0.637	0.356	0.115	0.295	0.286	0.305

Notes: The unit of observation is the municipality-month. The dependent variable is listed in the column the header. Observations lacking disbursed loans in columns 1-4 and 7, and outstanding loans in columns 5-6 are excluded from the sample. Columns 1-4 calculate the share of disbursed loans that entered into periods of 30 or 120 days past due within the first year after disbursement (columns 1 and 3) or during the first two years after disbursement (columns 2 and 4). Columns 5-6 calculate the share of outstanding loans per municipality-month that are 30 or 120 days past due. The outcome in column 7 is the share of loans for which we observe repayment more than 1.5 months beyond the original loan term. $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. All regressions include municipality and department-month fixed effects. Baseline controls include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses.*** p<0.01, ** p<0.05, * p<0.1.

Table A8: Cross-sectional Correlation of Municipal Characteristics Used for Heterogeneous Effects

	Access to		Land	Formal Land	Development
	Dpt. capital	Bogotá	Restitution	Ownership	Index
Access to Market	0.314***	0.595***	-0.104*	0.334***	0.367***
Access to Dpt. capital	-	0.065	-0.108*	0.341***	0.324***
Access to Bogotá	-	-	-0.003	0.187***	0.322***
Land Restitution	-	-	-	-0.131*	-0.135**
Formal Land Ownership	-	-	-	-	0.39***

Notes: This table shows correlations between time-invariant municipal characteristics. Access to wholesale market, to the departmental capital and to Bogotá based on distance in kilometers. Total applications for land restitution per 10,000 inhabitants since 2011. Formal land ownership is averaged over 2000-2008. The development index is the share of the population not considered to be poor according to the index of Unmet Basic Needs (UBN) in the 2005 census. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9: Other Heterogeneous Effects

	Heterogeneity based on:					
	Extensive margin		Above/below Median			
	PDET	FARC camps	Soil quality		Other Armed Groups	
			Accretion	Suitability	1987-2008	2009-2014
	(1)	(2)	(3)	(4)	(5)	(6)
$FARC_i$ x $Negotiations_t$ (Low) [a]	0.763	0.620	0.339	0.561	0.387	0.593
	(0.774)	(0.651)	(0.694)	(0.886)	(0.888)	(0.729)
$FARC_i$ x $Negotiations_t$ (High) [b]	0.132	-0.413	0.773	0.552	0.729	0.489
	(0.909)	(1.765)	(0.958)	(0.775)	(0.811)	(0.849)
$FARC_i$ x $Agreement_t$ (Low) [c]	2.637***	2.400***	2.420***	2.910***	2.568**	2.277***
	(0.936)	(0.763)	(0.855)	(1.011)	(1.088)	(0.862)
$FARC_i$ x $Agreement_t$ (High) [d]	1.581*	0.615	2.335**	1.749*	2.073**	2.399***
	(0.875)	(1.237)	(1.102)	(0.911)	(0.903)	(0.912)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,104	148,104	146,784	146,784	148,104	148,104
R-Squared	0.707	0.707	0.707	0.707	0.707	0.707
Mean DV	17.963	17.963	17.963	17.963	17.963	17.963
p-value H_0: [c] = [d]	0.366	0.156	0.947	0.339	0.708	0.909
p-value H_0: [b] = [d]	0.013	0.438	0.031	0.078	0.034	0.004

Notes: The unit of observation is the municipality-month. In column 1, FARC municipalities with a Post-conflict Development Program, *Programa de Desarrollo con Enfoque Territorial* (PDET) are classified in the high group. In column 2, FARC municipalities hosting a grouping camp for former FARC members after their demobilization are classified as high. In columns 3-6, we divide FARC municipalities into equally-sized groups (i.e. above/below median) based on the variable in the header. We adjust all of these variables, so that high corresponds to a desirable attribute. In columns 3-4 we use measures of soil quality. In columns 5-6, other armed groups include right-wing paramilitary militias, other left-wing insurgents (ELN, EPL, etc.) and other unknown armed groups. $FARC_i$ is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. $Negotiations_t$ is a dummy for months between June 2011 and October 2016 (both inclusive). $Agreement_t$ is a dummy for months on or after November 2016. The sample period is January 2009 to December 2019. All regressions include municipality and department-month fixed effects. Baseline controls include month fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Nighttime Luminosity

	ln(lights)	
	(1)	(2)
FARC_i x Agreement_t	0.231***	0.140***
	(0.039)	(0.025)
Municipality FE	Yes	Yes
Department x Time FE	Yes	Yes
Baseline controls	Yes	Yes
Time unit	Month	Quarter
Observations	104,346	34,782
R-Squared	0.864	0.945
Mean DV	-1.556	-1.33

Notes: In column 1 the unit of observation is the municipality-month. In column 2 the unit of observation is the municipality-quarter. The dependent variable is the log of nighttime lights. FARC_i is a dummy for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. Agreement_t is a dummy for months on or after November 2016. Sample period: April 2012-December 2019. All regressions include municipality and department-time fixed effects. Baseline controls include time fixed effects interacted with (i) dummies for quartiles of the distribution of rural share of population in 2005, (ii) dummies for varying percentiles of the distribution of the average share of municipal land dedicated to cultivation of 10 different crops between 2000-2008, (iii) a dummy for municipalities with a positive share of land dedicated to coca cultivation between 2000-2008. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix B Data Appendix

This data appendix describes in detail the different data sets we use in the paper and the construction of the different samples. We also provide detailed explanations of the variables we use.

B.1 Construction of the Samples

This sectio describes the construction of the different samples used in the paper. The following datasets contain information from Banco Agrario de Colombia. They are defined at the municipality-month level: 1) Panel of loan applications. 2) Panel of loan applications in scoring models. 3) Panel of disbursed loans. 4) Panel of loan repayment. 5) Panel of inspection visits. At the municipality-branch-month level we use: 6) Panel of loan applications (branch level).

Additionally, we use the following datasets which contain information on Colombian municipalities: 7) Universidad del Rosario database on the Colombian civil conflict. 8) CEDE panel database on municipal characteristics. 9) Database on land restitution applications.

1. Panel of loan applications: We begin with a loan-level dataset of all applications made by small farmers in the period 2005-2019. This contains a total of 4,739,631 observations. For each application, we observe the date of creation, the loan size, the loan's purpose, the destination municipality, the office in which it was created, and the client's ID. Although we observe applications since 2005, we exclude observations before 2009 because they lack information on the loan's destination municipality. This leaves us with a potential sample of 4,014,378 individual loan applications between 2009 and 2019. However, we must further drop 279,951 applications that either lack information on the destination municipality or have a code that refers to a non-existent municipality. We end up with 3,734,427 individual loan applications, which we then group at the municipality-month level. We use the loan's destination municipality and the month in which the application was created. We merge this data with a balanced monthly panel of all Colombian municipalities between 2009 and 2019. There are a total of 1,122 municipalities. The final panel of loan applications has 148,104 municipality-month observations.

2. Panel of loan applications in scoring models: Since mid-2012, BAC introduced scoring models to analyze the credit applications of small farmers. The applications are matched to each of the four available scoring models according to the intended purpose of the loan: for short-cycle crops, long-cycle crops, livestock, or other non-agricultural enterprises. Importantly, the datasets involved contain information not available in the Panel of Loan Applications described above. We use a dataset that contains loan-level information of all the loans that go through the scoring models between July 2012 and February 2019. This contains a total of 2,105,369 loans. For each application, we observe the client's yearly income, value of assets, level of education, months of experience in the productive activity, farm size, and credit bureau score. However, we restrict the sample to observations with complete information on all non-agricultural variables. This leaves us with a total of 2,084,439 loans. We merge this data with their corresponding loan application to obtain the destination municipality and the month of each application. We further drop 42,132 observations that lack information on the loan's destination municipality, which restricts the sample to 2,042,307 loans. We then group the loans in the scoring models at the municipality-month level. We merge this data with a balanced monthly panel of all Colombian municipalities between July 2012 and February 2019. Observations lacking loan applications in scoring models are dropped from the sample. We end up with a total of 84,372 municipality-month units.

3. Panel of disbursed loans: We begin with a sample of all the loans disbursed to small farmers in the period 2005-2019. This contains 3,647,151 individual disbursements. For each observation, we observe the date of the disbursement, the amount disbursed, the loan's maturity, the interest rate, and the type of collateral. We merge these disbursements with their corresponding loan application to obtain the month of the application. We restrict the sample to loans whose application was made during or after January 2009, which leaves us with 3,039,336 disbursements. However, we further drop observations that lack information on the loan's destination municipality, ending up with a final sample of 2,975,941 disbursements. Then we group the disbursements at the municipality-month level, using the destination municipality and the month of the loan application. We merge this data with a balanced monthly panel of all Colombian municipalities between 2009 and 2019. Observations without disbursed loans are excluded from the sample. We end up with a total of 133,576 municipality-month units.

4. Panel of loan repayment: We begin with a dataset at the loan-month level in which we observe the number of days past due for each loan in the sample of disbursed loans between January 2005 and December 2019. We observe every loan from the first month after disbursement until the last month in which the borrower paid the debt. Initially, we observe this information for a total of 3,620,322 disbursements. For each individual loan, we define dummy variables equal to one if during the first 12 or 24 months after disbursement the loan ever entered into a period of 60 or 120 days past due. We merge these dummies with their corresponding disbursements to obtain the investment municipality and the month of the application. We restrict the sample to loans whose application was made during or after January 2009, which leaves us with 3,038,660 loans. We further drop 63,389 disbursements that lack information on their destination municipality. Finally, we drop loans disbursed during or after January 2018 in order to restrict the sample to loans for which we observe their monthly repayment at least for 24 months after disbursement. We end up with a final sample of 2,357,622 loans. We aggregate the disbursements at the municipality-month level and calculate within each unit the share of loans that entered into different periods of overdues. We exclude units lacking loans disbursed. We end up with a panel of 108,470 municipality-month observations between January 2009 and December 2017.

5. Panel of inspection visits: In order to provide subsidized loans for agriculture, BAC uses funds from the Agricultural Financing Fund (*Fondo para el Financiamiento del Sector Agropecuario*, FINAGRO). This is a public second-tier bank that lends resources to first-tier banks. To ensure its funds are being adequately used, FINAGRO requires BAC to do in-person visits to the investment sites of 10% of the loans that use its resources. These are randomly selected every month from the pool of loans disbursed in the previous month. Clients have 180 days after the disbursement to invest the funds. After this period, randomly chosen clients are contacted by a BAC officer to schedule an inspection visit.

During the visit, the officer verifies whether the client's investment was in accordance with the size and intended purpose of the loan. The client must demonstrate this with supporting documents such as purchase invoices, or by directly showing the purchased or produced goods (machinery, infrastructure, crops, animals, etc.). To minimize the risk of collusion between the officer and the client, the former must fill an audit report stating whether he found any irregularity and, if so, what type of irregularity was found. This must be supported with photographic records of the evidence provided by the farmer.

Initially, we begin with a loan-level dataset of all inspection visits conducted between 2010 and 2018. This contains a total of 523,658 visits. For each audited loan, we observe the date of the visit and an indicator on whether the auditor found any irregularity during it. Irregularities are grouped into the following categories: Inconsistencies in the value of the investment, inconsistencies in the quantity of goods purchased or produced with the loan, unauthorized change of the loan's purpose, unauthorized change of the investment site, diversion of resources, incomplete investment project, inability to produce supporting documents, inability to locate the client, or complete absence of the investment. For each loan, we define a dummy variable that equals one if the audit identified any of the aforementioned irregularities. Using the loan id, we merge this dummy with the corresponding loan application to obtain the destination municipality and the month of the application. We are only able to merge 434,059 visits. From these, we further drop 14,477 visits that lack information on the loan's destination municipality. We then group the audited loans at the municipality-month level and merge them with the panel of disbursed loans. Before July 2011 and after August 2018, only 2% of loans were audited. Between these dates, however, between 8% and 36% of loans were audited. Therefore we restrict the panel to audits for loans created between July 2011 and August 2018. Units without disbursed loans that could be audited are also excluded from the sample. We end up with a total of 418,601 audited loans, grouped into 88,931 municipality-month units.

6. Panel of loan applications (branch level): We begin with a dataset of all applications made by small farmers in the period 2005-2019, which contains 4,739,631 loans. We exclude observations before 2009 because they lack information on the loan's destination municipality. Additionally, we drop loans created after this date that have incorrect municipality codes. This leaves us with a sample of 3,734,427 applications. Then, we group the loan applications at the branch-municipality-month level. We use the loan's destination municipality and the month in which the application was created. We merge this data with a monthly panel of municipality-branch combinations between 2009-2019. We use two approaches to define the municipality-month combinations in the panel: i) Using all combinations with non-zero loan applications at some point between 2009-2019. ii) Using only combinations with non-zero applications at some point before 2016. In the first case, we end up with a sample of 2,172,574 branch-municipality-month units. In the second one, the final sample consists of 1,771,176 units. In both cases, we assume the branch is open from the first month in which we observe an application until the end of the sample period.

7. Universidad del Rosario database on the Colombian Civil Conflict: This is an event-level dataset that records conflict events between 1996 and 2014 involving different agents in the Colombian conflict. For each event, the dataset records the the type (clash or attack), the agent involved (left-wing guerrillas, right-wing paramilitaries, government forces, others), the date, and the municipality of occurrence. For each municipality, we aggregate the total number of conflict events involving FARC between 1996 and 2008. For our main measure of exposure to FARC, we define a dummy that equals one for municipalities that rank above the 75% percentile of aggregate FARC events. We then merge this information with the panel of Colombian municipalities.

8. CEDE panel database on municipal characteristics: This data set contains panel data at the municipality-year level on various characteristics of Colombia municipalities between 1984 and 2018. This data is provided by the research center CEDE (*Centro de Estudios sobre Desarrollo Económico*) at Universidad de los Andes, which collects the information from multiple government agencies. For each municipality, the panel contains yearly information on agricultural, geographical, and demographic characteristics. In addition, it contains yearly data on civilian exposure to armed conflict, which is taken from the Colombian Registry of Victims.

9. Database on land restitution applications: This information comes from the Colombian Land Restitution Unit. This government agency was created by the *Victim's Bill* signed by President Santos in 2011. Its main purpose is to guarantee the restitution of land to people who were forcibly displaced during the civil conflict. For each municipality, this database contains the aggregate number of restitution applications made between 2011 and 2019 for property located in each municipality.

B.2 Variable Definitions

1. Variables in the Panel of Loan Applications:

- Loan applications per 10,000 inhabitants: Defined as the number of monthly loan applications intended for each destination municipality, normalized by the municipality's population in 2008.
- Share female: Loans from women applicants as percentage of total loan applications at the municipality-month level.
- Average age: Average years of age of applicants at the municipality-month level.
- Share new: Clients are classified as new if between 2005 and the date of their current application they had no loan applications in the BAC data. The variable is defined as the share of monthly loan applications in each destination municipality created by new clients.
- Average loan size: Measured in millions of 2019 COP. Average amount borrowers apply for at the municipality-month level.
- Share agricultural: Loan applications intended for agricultural purposes as percentage of total loan applications at the municipality-month level.
- Share of applications in-the-field: In order to offer financial services the bank organizes brigades in which loan officers visit farmers or places far away from BAC branches.

For loan applications between January 2009 and December 2017, we observe a variable indicating whether they were generated in these field programs. We calculate the number of applications in-the-field as percentage of total loan applications per municipality-month between 2009 and 2017.

2. Variables in the Panel of Loan Applications in Scoring Models:

- Applications per 10,000 inhabitants: Number of loan applications in scoring models at the municipality-month level, normalized by the municipality's population in 2008.
- Share of applications in scoring models: Loan applications in scoring models as percentage of total loan applications, both grouped at the municipality-month level.
- Secondary education: Loans from applicants whose highest qualification is secondary education as percentage of total loan applications in scoring models at the municipality-month level.
- Tertiary education: Loans from applicants whose highest qualification is tertiary education as percentage of total loan applications in scoring models at the municipality-month level.
- Previous experience: Measured in months. Refers to the applicant's previous experience working in their productive activity. Defined as the average number of months of working experience reported by loan applicants, grouped at the municipality-month level.
- Average assets: Measured in millions of 2019 COP. Average worth of the assets owned by loan applicants grouped at the municipality-month level.
- Average yearly income: Measured in millions of 2019 COP. Average yearly income received by loan applicants grouped at the municipality-month level.
- Farm area: Measured in hectares. Average farm size of loan applicants at the municipality-month level. This information is only available for farmers who apply for agricultural loans.
- Share of applications with credit score: Percentage of loan applications at the municipality-month level whose clients have a non-missing credit bureau score. Applicants without credit history lack this information.
- Average credit score: Defined only for loan applications whose applicant has a non-missing credit bureau score. Calculated as the average score across applications from the same municipality and month, on a scale from 0 to 1000.

3. Variables in the Panel of Disbursed Loans:

- Loans disbursed per 10,000 inhabitants: Monthly number of loans disbursed in each destination municipality, normalized by the municipality's population in 2008.

- Approval rate: Disbursed loans as percentage of total loan applications, both grouped at the municipality-month level.

- Average loan size: Measured in millions of 2019 COP. Average amount disbursed at the municipality-month level.

- Total disbursements per 10,000 inhabitants: Measured in millions of 2019 COP. Defined as the total amount of money disbursed at the municipality-month level, normalized by the municipality's population in 2008.

- Average interest rate: Refers to the number of points above the benchmark interest rate in Colombia, the DTF, which is the reference rate used by BAC. The variable we use is the average across applications from the same municipality and month. The DTF is the average of the interest rates on 90-day Certificates of Deposits offered by Colombian banks.

- Share of loans with government collateral: Percentage of disbursed loans at the municipality - month level whose collateral comes from state guarantee funds, such as the Agricultural Guarantee Fund (*Fondo Agropecuario de Garantías*) and the National Guarantee Fund (*Fondo Nacional de Garantías*).

- Share of loans with own assets as collateral: Percentage of disbursed loans at the municipality-month level whose collateral comes from the client's personal assets, such as mortgages, vehicles, machinery, etc.

- Share of loans with maturity ≤ 2 years, between 3-5 years or ≥ 5 years: Loans with maturities between these ranges, as percentage of total disbursements at the municipality-month level. The maturity is the date on which the client's final payment of the loan is due. This is predetermined at the time of the disbursement.

4. Variables in the Panel of Loan Repayment:

- Share of disbursed loans with 60 days past due (Year 1): Loans that entered in a period of 60 days past due during their first year after disbursement, as percentage of total loans disbursed in each municipality-month unit.

- Share of disbursed loans with 60 days past due (Years 1-2): Loans that entered in a period of 60 days past due during their first two years after disbursement, as percentage of total loans disbursed in each municipality-month unit.

- Share of disbursed loans with 120 days past due (Year 1): Loans that entered in a period of 120 days past due during their first year after disbursement, as percentage of total loans disbursed in each municipality-month unit.

- Share of disbursed loans with 120 days past due (Years 1-2): Loans that entered in a period of 120 days past due during their first two years after disbursement, as percentage of total loans disbursed in each municipality-month unit.

- Extended payments: For loans with maturities up to two years, we define a dummy that equals one if we observe the client took more than 1.5 months after the maturity date to finish repaying the loan. We group these loans at the municipality-month level, and calculate the share of loans in each unit that required extra months of repayment.

5. Variables in the Panel of Inspection Visits:

- Share of disbursed loans with inspection visits: Loans with inspection visits in each municipality-month unit as percentage of total disbursements per unit.

- Share of visits with irregularities: Visited loans in which the auditor found any irregularity in the use of the funds, as percentage of total disbursements per municipality-month.

6. Variables in the Panel of Loan Applications (branch level):

- Loan applications per 10,000 inhabitants: Defined as the number of loan applications grouped at the municipality-branch-month level, normalized by the municipality's population in 2008.

7. Variables in Universidad del Rosario Data on the Colombian Civil Conflict:

- Exposure to FARC (main treatment variable): Dummy that equals one for municipalities in the upper quartile of total conflict events involving FARC between 1996 and 2008, normalized by the municipality's population in 2008.

- Exposure to FARC (continuous measure): Total conflict events per municipality involving FARC between 1996 and 2008, normalized by the municipality's population in 2008.

- Exposure to other armed groups: For each municipality, we calculate the total number of conflict events involving armed actors different from FARC. These include right-wing paramilitary groups, other left-wing guerillas, or other unknown armed actors. We calculate the number of events per municipality in the following two periods: i) 1996-2008. ii) 2009-2014. Then we normalize the number of events by the municipality's population in 2008.

- Exposure to armed conflict: Total conflict events per municipality involving any armed actor or government forces between 1996 and 2008. Normalized by the municipality's population in 2008.

8. Variables in the CEDE Panel Database on Municipal Characteristics:

- Population: Total number of inhabitants per municipality in 2008.

- Share of rural population: Inhabitants living in rural areas of the municipality as percentage of total inhabitants, both measured in 2008.

- Share of land devoted to the 10 main crops in the country: For each municipality, we calculate the yearly share of land dedicated to the cultivation of coffee, rice, sugarcane, plantain, oil palm, yucca, potatoes, cocoa, beans, and corn between 2000 and 2008. Then, for each municipality, we calculate the average share of land dedicated to each crop across years. For each crop, we define the following variables according to the distribution of their share of land: For potatoes, rice and oil palm, less than 25% of municipalities grow each one, so we define dummies that indicate if the average share of land dedicated to each crop is positive. For the remaining crops, at least 40% of municipalities cultivate each. We split the positive values into two same-sized groups and leave the zeros apart. We define dummy variables denoting this partition for each crop. The only exception is corn, which is grown in 89% of municipalities. In this case, we define quartiles of the share of land devoted to its cultivation.

- Share of land dedicated to coca cultivation: For each municipality, we calculate the average share of land dedicated to the cultivation of coca crops between 2000 and 2008. We define a dummy that equals one if the average share is positive for each municipality. This accounts for roughly 25% of municipalities.

- Access to wholesale market: Linear distance between the municipality centroid and the closest wholesale market. Measured in kilometers. Treatment municipalities are classified as as having high access to wholesale markets if their distance to the closest one is less than the sample median within the treatment group.

- Access to the departmental capital: Linear distance between the municipality centroid and the department's capital. Measured in kilometers. Treatment municipalities are classified as as having high access to the departmental capital if their distance to it is less than the sample median within the treatment group.

- Access to Bogotá: Linear distance between the municipality centroid and Bogotá. Measured in kilometers. Treatment municipalities are classified as as having high access to Bogotá if their distance to this city is less than the sample median within the treatment group.

- Share of non-poor: According to the index of Unmeet Basic Needs (UBN), which is calculated with data from the 2005 census. Treatment municipalities are classified as having a low share of non-poor inhabitants if their UBN index is higher than the sample median within FARC municipalities.

- Equal land ownership: GINI index per municipality, measured in 2008. The information was provided by the Geographical Institute Agustin Codazzi. Treatment municipalities are classified as having low equality in land ownership if their GINI index is higher than the sample median within FARC municipalities.

Additionally, the CEDE database contains information on civilian exposure to armed conflict between 1993 and 2018. These variables are calculated from data provided by the Colombian Registry of Victims:

- Land theft: Yearly number of victims per municipality whose land was stolen during the armed conflict, normalized by the municipality's population in 2008.
- Terrorism: Yearly number of victims of terrorists acts per municipality, normalized by the municipality's population in 2008.
- Threats: Yearly number of people threatened by armed actors per municipality, normalized by the municipality's population in 2008.
- Sexual violence: Yearly number of victims of sexual aggression per municipality, normalized by the municipality's population in 2008.
- Forced disappearances: Yearly number of victims of forced disappearance per municipality, normalized by the municipality's population in 2008.
- Forced displacement: Yearly number of victims forcibly displaced from their properties, normalized by the municipality's population in 2008.
- Homicide: Yearly number of killings related to the armed conflict per municipality, normalized by the municipality's population in 2008.
- Land mines: Yearly number of victims of land mines per municipality, normalized by the municipality's population in 2008.
- Property loss: Yearly number of victims per municipality who reported loss of property due to the armed conflict, normalized by the municipality's population in 2008.
- Kidnapping: Yearly number of kidnapped people per municipality, normalized by the municipality's population in 2008.
- Torture: Yearly number of torture victims per municipality, normalized by the municipality's population in 2008.
- Underage recruitment: Yearly number of children recruited by armed conflict actors, normalized by the municipality's population in 2008.
- Family of outcomes: Average of the standarized variables of civilian exposure to armed conflict.

9. Variables in the Database on Land Restitution Applications:

- Land restitution applications: Number of applications made between 2011 and 2019 for restitution of properties located in each municipality. Treatment municipalities are classified as having low restitution applications if theirs is lower than the sample median within FARC municipalities.