Forgone Investment Amid Conflict: Evidence from Credit Microdata in Colombia*

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Abstract

We study the causal effect of conflict on investment using a unique administrative dataset from a large bank serving rural producers in Colombia. Our difference-in-difference strategy exploits the 2016 peace agreement between the Colombian government and insurgent group FARC, combined with pre-existing differences in FARC exposure across municipalities. We show that the number of business loans increases in municipalities with historical FARC presence after the peace agreement. More loan applications drive this increase, with no change in supply-side variables. However, higher investment is only observed in municipalities located close to markets and does not materialize before the peace agreement is finalized, despite a large decline in violence during the preceding negotiations period. A simple theoretical framework combined with rich information on the characteristics of loan applicants and projects (including credit scores and delinquency rates), as well as night-time lights, suggests that conflict hinders investment mostly by lowering project returns.

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1 Introduction

Seminal work by Coase (1960), Demsetz (1967) and North (1981) suggests that weak property rights and high transaction costs lead to a misallocation of resources. These issues are particularly prominent in areas exposed to the violent contestation of power by armed groups, which plausibly leads producers to forgo otherwise profitable investments due to fear for their life or property. However, previous research has shown that certain economic activities actually appear to thrive under conflict as a result of weak state oversight (Guidolin and La Ferrara, 2007). Moreover, armed groups often serve as a substitute for the state in the adjudication of disputes or the provision of public goods (Berman and Matanock, 2015). Under these circumstances, the end of conflict could in fact lead to a deterioration in the institutions that facilitate economic activity and may prove detrimental to investment. The relationship between conflict and investment is ultimately an empirical question. The answer to this question has important implications for the prospect of peace and long-term economic growth in conflict-ridden areas (Blattman and Miguel, 2010).

Until now, the study of this topic has presented an insurmountable measurement challenge due to the limited availability of high-quality information on investment decisions by producers in conflict areas. Even in the presence of such information, additional difficulties arise in disentangling a low willingness to invest from market imperfections that limit the supply of credit in rural parts of the developing world (Banerjee, 2003; Conning and Udry, 2007). Furthermore, the non-random nature of conflict presents an additional challenge for the identification of its causal effect on investment. Armed groups predominantly operate in remote areas with limited access to markets, factors themselves that hinder economic activity (Fearon and Laitin, 2003; Donaldson, 2015). Whether conflict is the binding constraint on investment under such conditions is far from certain (Rodrik, 2010).

In this paper, we study the effect of civil conflict on investment using administrative data from *Banco Agrario de Colombia* (BAC), a large public bank serving rural producers in Colombia. BAC is the main source of credit for small producers in rural areas, representing 97% of formal loans in 2013. Our dataset includes the universe of the bank's business loans between 2009 and 2019 (2.9 million). These correspond to 1.7 million applicants, equivalent to 64% of the country's agricultural producers. Besides its extensive coverage, our data has other unique features. First, we observe credits starting at the application stage, which allows us to better distinguish changes in the demand for credit from changes in the supply. Second, the availability of detailed information on applicants and loans, including credit scores, audit reports and delinquency rates, allows us to study different mechanisms through which conflict may affect investment, as well as to detect changes in the quality of loans.

We leverage variation in conflict arising from the peace agreement signed by the Colombian government and the insurgent group FARC in 2016. FARC was the main guerrilla group in the civil conflict that ravaged the Colombian countryside for over 50 years, with an estimated death toll of more than 200,000 victims (GMH, 2013). Using an event-level dataset, we classify municipalities as having high historical exposure to FARC (henceforth referred to as FARC municipalities) if they rank in the top quartile of aggregate FARC activity per 10,000 inhabitants between 1996 and 2008 (i.e., before the start of our sample period). These years correspond to the most violent period in the history of the Colombian conflict and allow for a meaningful assessment of the exposure to conflict across municipalities.

Our difference-in-difference research design compares credit outcomes in municipalities with varying FARC exposure, before and after the conflict ends. All our regressions include municipality and department-month fixed effects. The former account for persistent differences across municipalities, while the latter account for time-varying factors that affect all municipalities in the country or that vary across departments. Our preferred specification accounts for imbalance in predetermined covariates by including time dummies interacted with a battery of predetermined municipal characteristics, such as the rural share of the population, and the share of land devoted to the cultivation of various different crops, including illegal narcotics. Alternatively, we use LASSO regressions to optimally select the set of controls or propensity-score weights to increase comparability (Hirano and Imbens, 2001).

The identifying assumption is that the difference in outcomes between municipalities with varying FARC exposure should remain stable in the absence of the peace deal. We incorporate potential anticipatory effects by distinguishing between a pure pre-period, the earlier *negotiations* phase, and the period after the final peace *agreement* was signed in November 2016. We set the start date for the interim negotiations period in June 2011, when Congress approved landmark legislation allowing victims of the conflict to receive reparations from the state and to seek land restitution. This was the earliest indication of the national government's renewed peace effort, but our results are robust to alternative definitions, including the actual announcement of the start of peace negotiations in September 2012. We show that FARC municipalities experience a sizable decrease in violence during the negotiations period, which persists into the agreement period.

Our main results show that investment increases in FARC municipalities after the final peace agreement, as reflected by more loan applications and disbursed loans. We estimate a relative increase of 19 million COP ($14,500 at the PPP-adjusted exchange rate) in monthly loan disbursements per 10,000 inhabitants in these municipalities, equivalent to a 17% increase over the sample mean. Importantly, these effects only materialize after the peace deal is finalized, but not during the preceding negotiations phase, despite the sharp drop in violence. This suggests that expectations about renewed conflict affect investment decisions to a much larger degree than the contemporaneous level of violence, in line with evidence by Besley and Mueller (2012) for Northern Ireland. We also find that the increase in investment is concentrated in FARC municipalities located close to wholesale markets, their department capital, or Bogotá. This suggests that conflict is not the binding constraint on investment in very remote areas with limited market access.

To guide our analysis of mechanisms, we develop a stylized model in which a producer faces a costly investment opportunity with an uncertain payoff. The model highlights several potential channels through which conflict may reduce investment, including a higher cost of investment, a lower *return* if the project succeeds, or a lower probability of project success (i.e., higher *risk*). Another possibility is that conflict affects relevant characteristics of producers, such as levels of risk aversion or initial wealth. We leverage the rich information on the characteristics of applicants and loans, including credit scores and delinquency rates, as well as data from other sources (e.g., night-time lights), to shed light on these mechanisms.

Explanations of our findings based on changes in supply-side factors find little support in the data. Our results are not driven by changes in the location or the operation of BAC branches. We observe no change in loan approval rates, neither aggregated at the municipality level nor at the individual level controlling for observable characteristics. Interest rates likewise remain unchanged. We further verify that the results are not driven by municipalities included by the central government in special plans for targeted investments amid the implementation of the peace agreement. Combined with the documented increase in loan applications, these results strongly suggest that the overall increase in investment is driven by a higher willingness to invest rather than by changes in the supply of credit.

Changes in the composition of the loan applicant pool also fail to explain our results. Though we lack a direct measure of applicants' level of risk aversion, we find no change in some demographic characteristics that correlate with risk aversion, such as gender or age (Charness and Gneezy, 2012; Dohmen et al., 2017). We find, however, an increase in the share of applicants that are new BAC clients, as well as a slight decrease in average applicant wealth. These results suggest that peace has positive effects on financial inclusion and that it disproportionately benefits less wealthy individuals (i.e., a progressive policy).

We also find that the share of loans relying on a government guarantee decreases in FARC municipalities after the peace deal. This indicates higher reliance on own collateral. Relatedly, the documented increase in credit demand is somewhat higher in FARC municipalities with more applications for land restitution in the context of the 2011 Victims Bill, though the difference is not statistically significant. This suggests a complementarity between peace and formal access to land. However, the magnitude of the land restitution program is too small to explain the increase in credit demand that we document.

We similarly find no change in multiple proxies for the probability of project success (i.e., risk), including credit scores and delinquency rates for new or outstanding loans over multiple time horizons. Using additional information from in-person audits of investment sites, we show that the share presenting irregularities also remains unchanged. These results show that conflict does not affect the riskiness of investment. They also suggest that the large increase in credit caused by the peace deal did not worsen the quality of BAC's portfolio.

Conflict may also hinder investment by reducing project returns. In this regard, our finding of a heterogeneous effect of peace based on market access is consistent with an increase in returns that is insufficiently high in very remote areas. This hypothesis is also consistent with a large body of qualitative evidence showing that FARC engaged in systematic *taxation* of local producers in its areas of operation (Arjona, 2016; Gilbert, 2022). Peace could also increase project returns by leading to a boom in local economic activity (for instance, via looser restrictions on mobility or business hours). Though GDP data is unavailable at the municipality level, we use VIIRS data on night-time lights (NTL) to construct a high-frequency proxy for local economic activity (Henderson et al., 2012). We show that NTL increases 14% in FARC municipalities after the peace deal. Leveraging data on loan characteristics, we further document an increase in the share of loans with maturity above 5 years and in the share corresponding to investment (rather than working capital). This suggests that projects with long time horizons and low discounted present value that were previously forgone are now being found sufficiently profitable. Taken together, this body of evidence lends support to changes in project returns as the main driver of our results.

This paper contributes to the burgeoning literature on the economics of civil conflict (Blattman and Miguel, 2010). Previous work on the impact of conflict on economic activity has documented negative effects of urban terrorism in developed countries (Abadie and Gardeazabal, 2003; Besley and Mueller, 2012).[1] The link between conflict and investment has been the focus of a small number of studies documenting changes to productive activities and asset holdings as coping mechanisms for violence (Deininger, 2003; Verpoorten, 2009; Arias et al., 2019; Blair et al., 2022). These studies have largely relied on surveys and have struggled to establish causality. In this regard, our setting and data provide a unique

[1] A large literature has documented a negative impact of conflict on various dimensions of human capital (e.g., Camacho, 2008; Akresh et al., 2012; Mansour and Rees, 2012; León, 2012). A separate and growing body of work has studied the effect of conflict on trust and cooperation (Bauer et al., 2016). Another strand of literature looks at the long-run impact of large-scale bombing (Davis and Weinstein, 2002; Miguel and Roland, 2011; Riaño and Valencia Caicedo, 2020).

opportunity to overcome the measurement and identification challenges that have hindered academic progress in this area. We make three contributions to this literature. First, we combine detailed credit microdata with a natural experiment to document a positive causal effect of peace on the willingness to invest of small rural producers.[2] Second, we show that this increase in investment materializes only after the uncertainty about renewed violence is resolved and only in localities that are sufficiently close to markets. Third, we leverage the richness of the data to show that conflict hinders investment mostly via lower project returns. Our findings have important policy implications for conflict and post-conflict settings, including the complementarity between peace, access to markets, and secure land tenure.

Our paper also speaks to the large literature studying the challenges faced by agricultural producers in developing countries (Banerjee, 2003; Conning and Udry, 2007). This literature has identified different forms of risk, such as weather variability (Rosenzweig and Wolpin, 1993; de Roux, 2021) or price fluctuations (Fafchamps, 1992; Burke et al., 2019), that shape production and investment decisions. Previous research has also shown that 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 the investment decisions of rural producers in developing countries. We also provide evidence on the interaction between conflict and other factors affecting investment, such as land restitution and market access.

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, heterogeneous effects, and robustness checks. Section 5 presents a simple model of investment and our discussion of mechanisms. Section 6 concludes.

2 Background

2.1 The Colombian Conflict

FARC was a Marxist insurgency created in 1964.[3] It originated from peasant self-defense groups dating back to the late 1940s, a period of intense violence between the Liberal and Conservative parties. Early in its history, FARC operated in remote rural areas, extorting

[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., 2021; Prem et al., 2020, 2021, 2022).

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

local farmers for subsistence and waging a low-intensity war against the government. The group expanded rapidly in the 1990s thanks to its growing involvement with the drug trade and had as many as 20,000 troops by the year 2000 (Dube and Vargas, 2013). A series of FARC military victories prompted then President Andrés Pastrana (1998-2002) to engage in peace negotiations with the group, which ultimately failed in 2002. This was the most violent period in the Colombian conflict, involving left-wing insurgencies, government forces, and right-wing paramilitary groups. 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. Between 1985 and 2005, 45% of years are classified as civil war (1,000+ deaths).

Pastrana's successor, 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 to the rescue of its most high-profile hostages (Fergusson et al., 2014). Uribe's successor, Juan Manuel Santos (2010-2018), announced a new round of peace talks with FARC in September 2012. This 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 two of FARC's top commanders, *Mono Jojoy* and *Alfonso Cano*. However, the Santos government had also begun to show signs of a renewed attitude toward the conflict since June 2011, when Congress approved a landmark *Victims bill* that allowed civilians affected by violence to seek reparations from the State.[4] The bill also enabled people that were forcibly displaced from their land to seek restitution of their property.

The new round of peace talks focused on a pre-specified 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. Most of the negotiations took place amid continued fighting, except for a few short-term ceasefires on occasions such as the Christmas holiday 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 (e.g., BBC News, 2014). Despite these issues, an agreement was reached over the first two points in 2013, over drug trafficking in 2014, and over victims in 2015. Still, the negotiations took place under the premise that the government would only accept a full agreement, which added uncertainty over the final outcome (Santos, 2019). The fact that several previous attempts at peace had failed also invited to prudence.[5] In

[4]The Victims Bill (Law 1148 of 2011) formally acknowledges the existence of an internal armed conflict in Colombia and recognizes the responsibility of the state towards the victims.

[5]Besides Pastrana's, 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 the political party *Unión Patriótica* as a FARC offshoot, which was targeted and decimated by right-wing paramilitary groups over

December 2014, FARC declared an indefinite 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 hostilities. The full text was submitted for popular approval through a plebiscite held in October 2016. Narrowly rejected ("No" won with 50.2% of votes), the agreement was partially modified to incorporate some of the concerns of its critics. The modified agreement was signed and ratified by Congress in November 2016, putting an end to over 50 years of violence and more than 200,000 deaths (GMH, 2013).

As part of the agreement, FARC committed to lay down its weapons, withdraw from drug trafficking and contribute to peace through truth-telling, reparations, and demining. The government agreed to provide temporary economic support to former combatants and to reserve a handful of seats in Congress for the group 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, improved access to credit, and investments in infrastructure. A total of 170 municipalities in 16 different regions were included in Regional Development Programs (*Planes de Desarrollo con Enfoque Territorial, PDET)* to target these investments. After the peace agreement, the vast majority of FARC members demobilized and the organization transitioned into a new political party that has participated in all elections since 2018, with the exception of some small splinter groups.

2.2 Agricultural Credit

The Colombian Agrarian Bank (*Banco Agrario de Colombia*, BAC) is Colombia's only first-tier public bank.[6] BAC's objective is to provide financial services to rural areas and its bylaws require it to allocate at least 70% of its credit portfolio to activities related to cultivation of crops, livestock, fishing, or forestry. Henceforth, we refer to these activities collectively as agriculture. BAC has extensive geographic coverage and reached 780 branches in 754 municipalities (67% of the total) by the end of our sample period in 2019 (7% growth since 2009). In contrast, some of the largest private banks have branches in fewer than 250 municipalities. Hence, BAC is often the only source of formal financial services in remote rural areas, where it faces only limited competition from informal lenders.[7]

the following years (Fergusson et al., 2020). The Gaviria peace talks were also unsuccessful.

[6]BAC was created in 1999 and is overseen by the Ministry of Agriculture. It replaced a previous financial institution called *Caja Agraria*, which dated back to the 1930s and had recently declared bankruptcy. All other first-tier public banks were privatized as part of a financial liberalization reform in the early 1990s.

[7]In 2016, 51% of respondents to a large rural survey (ELCA) reported having any form of credit: 36% had formal loans, 7% had semiformal loans (e.g., micro-finance), and 15% had informal loans (Laajaj and Parra, 2017). Even among those with informal land tenure (and any credit), the probability of having a formal loan was 11 pp (60%) higher than that of having an informal loan. DNP (2014) reports that total

A second-tier public bank called FINAGRO provides rediscount resources for most agricultural loans issued by BAC. Colombia's Law 16 of 1990 mandates a yearly forced investment by all private banks in low-return bonds issued by FINAGRO. These financial institutions can, however, replace a portion of this forced investment with direct lending for the agricultural sector. As a result, private banks specialize in medium and large clients, which are arguably less risky and more profitable, while BAC mostly serves small producers using FINAGRO's subsidized funding.[8] In 2013, 87% of FINAGRO's rediscount resources were allocated to BAC and the bank was responsible for 97% of loans to small rural producers nationwide (DNP, 2014). Among the loans in our sample, 67% use funds from FINAGRO. These loans can only be used for investments in agriculture (broadly defined) and have two noteworthy features. First, FINAGRO sets a cap on the interest rate that banks can charge. Second, FINAGRO requires in-person visits to the investment site for a representative sample covering at least 10% of loans to ensure that funds have been used appropriately.

The loan application process at BAC involves two stages. In the first stage, which usually takes place with the applicant at the branch, a bank officer makes a query to a credit bureau. The query results in a report that contains information on the credit history of the applicant and a credit score. It also indicates whether or not the application process can proceed.[9] Clients with no 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 loan officer also takes into account other aspects of the application, like the projected income flow of the project and some individual characteristics of the applicant.

BAC loans to small producers must be fully collateralized. If the applicant lacks sufficient collateral, the loan officer can determine eligibility for one of several guarantee schemes. For agricultural loans, FINAGRO offers a guarantee of up to 80% of the value of the loan through a fund called *Fondo Agropecuario de Garantías* (FAG). For non-agricultural loans, the national government offers a guarantee of also up to 80% through a separate fund called *Fondo Nacional de Garantías* (FNG). These guarantees have annual fees of 1-4% of the value of the loan, which provides an incentive for borrowers to use their own collateral when available. However, applicants often struggle to provide satisfactory documentation

BAC loans in 2012 were 2.3 times larger in value than credit provided by sellers of agricultural inputs.

[8]FINAGRO defines a small producer as having assets below 81 million COP (roughly 27,000 USD at the 2017 average exchange rate). Also, either 75% or more of the farmer's assets is dedicated to agriculture or at least two-thirds of the farmer's income comes from agriculture. In 2019, small producers represented 23% of the total agricultural loan volume (including BAC and other banks), but 93% of loan recipients.

[9]Denial occurs if the credit score is below a certain threshold or if the number of periods with overdues for previous loans exceeds a certain number. In our sample, 9% of applications are denied at this stage.

proving ownership of their property. Smaller complementary guarantees are available from subnational governments (i.e., departments) and from collective organizations such as the National Coffee Growers Association. In our sample, 75% of loans have a guarantee from the central government (67% have FAG) and 2.2% have a complementary guarantee.

Once a loan is disbursed, the borrower is reported to the credit bureaus if she is more than 30 days overdue, which negatively impacts the individual's credit history. If the loan has a FAG guarantee, the bank can reclaim the guarantee after more than 180 days overdue but must pursue legal restitution from the defaulting borrower in exchange, with the proceeds returning to FAG. A borrower that defaults also becomes ineligible 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. In our sample, 12% of outstanding loans per municipality-month are 30 days past due on average.

3 Empirical Strategy

3.1 Data

Our main source of information is 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 more easily disentangle the contribution of demand and supply to any observed changes in the total 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 hinder investment. Third, we can study the quality of the loans by studying both delinquency rates and the reports from in-person visits to investment sites.

We collect data on all business loan applications by small producers between 2009 and 2019.[10] We focus on small producers for three reasons. First, they constitute the bulk of BAC clients and have limited access to alternative sources of credit. This increases the likelihood that we pick up changes in the overall demand for credit rather than substitution across lenders. Second, small producers have weaker property rights and more immobile assets, which makes them more likely to be affected by conflict in their municipality. In contrast, larger producers can more easily reallocate their investments to other regions and can also invest more in security. Finally, only in the case of small farmers can we observe the

[10] Basic information is available for all applications throughout this period. The more detailed information that BAC uses for its credit analysis (which we use to study mechanisms) is only available since July 2012.

destination municipality for all loan applications, which is crucial for our research design.

Our sample includes 3.7 million applications and 2.9 million disbursed loans. These applications correspond to 1.7 million different applicants, 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 COP (roughly 7.3 billion USD).[11] For most of the analysis, we aggregate outcomes at the municipality-month level based on the destination municipality of each loan, and we normalize by municipal population in 2008 (i.e., before the start of our sample period). Appendix Table A1 provides summary statistics for our main outcomes of interest. On average at the municipality-month level, BAC receives 18 applications and disburses 14 loans per 10,000 inhabitants, for an approval rate of 78%. The average loan amount is 7.9 million COP (2,600 USD), while the average interest rate is 11.8%.[12] Roughly equal shares of loans have a maturity of 0-2 or 3-5 years (37% each), while the remaining 26% of loans have maturities longer than 5 years.

We measure municipalities' exposure to FARC using an event-based conflict dataset provided by Universidad del Rosario. This dataset covers the period 1996-2014 and records attacks and clashes. For each event, the dataset reports the municipality and date of occurrence, as well as the specific actors involved. 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 add all events per municipality up to 2008 and normalize by population in that year. We then define as exposed to FARC those municipalities (281) that rank above the 75th percentile of this variable, similarly to Acemoglu et al. (2013). We refer to these as FARC municipalities.

Our measure captures high historical exposure to FARC over a thirteen-year period that corresponds to the most intense phase of the Colombian conflict. While conflict events may be a better indicator of contestation than of armed group presence (Crost and Felter, 2019), the period we use to construct our measure of exposure includes FARC's most ambitious period of expansion in the late 1990s, as well as the Colombian military's aggressive counterinsurgent campaign from the early and mid-2000s, which specifically targeted FARC strongholds.[13] It

[11]Throughout the paper we express all monetary values in constant 2019 Colombian pesos (COP). When converting to US dollars (USD), we use a nominal exchange rate of 3,000 COP/USD (roughly the average daily exchange rate in 2017) and a PPP exchange rate of 1,315 COP/USD based on OECD estimates.

[12]Interest rates are defined as percentage points above a reference rate called DTF. This corresponds to the average return on 90-day fixed-term deposits, which averaged 4.9% during our sample period. FINAGRO sets a cap on interest rates for loans using its resources of DTF + 7%. In our sample, the average interest rate for Finagro-backed loans is DTF + 5.6%, while for loans using BAC's own resources it is DTF + 27.8%.

[13]Appendix Figure A1 shows that total FARC activity increased sharply between 1999-2002. This period corresponds to the unsuccessful peace process under President Pastrana, which included the creation of a demilitarized zone (42,000 km^2) that was effectively governed by FARC. Insurgent activity then steadily decreased until 2010. This decline reflects the success of the military campaign launched by the Uribe

is highly unlikely that a municipality with high historical exposure to FARC will have few conflict events during this period. We verify below that our results are robust to (i) different exposure thresholds, (ii) different durations of the exposure period, (iii) use of the continuous measure of exposure, or (iv) use of conflict data from an alternative source.

Since the conflict data from Universidad del Rosario ends in 2014, we complement it with data extending to 2019 from the government agency charged with implementing the Victims Bill (*Unidad para la Atención y Reparación Integral a las Víctimas*, UARIV), which we use to study conflict outcomes during our sample period. UARIV provides victim counts at the municipality-year level for 12 different conflict indicators, including kidnapping, terrorism, sexual violence, forced displacement, recruitment of minors, and homicide. To avoid incorrect inference from multiple hypothesis testing, we focus on an aggregate index that we construct by standardizing and averaging across these outcomes, following Kling et al. (2007). Unfortunately, the data from UARIV does not specify the armed group involved.

Appendix Figure A2 shows the spatial variation in our measures of conflict exposure and demand for credit. Panel (a) displays quartiles of the aggregate loan application rate during the sample period, while panel (b) shows the location of FARC municipalities. The loan application rate is highest in municipalities located in the mountainous areas near the center of the country, while FARC municipalities are mostly located in jungle areas in the south and west, as well as in border regions near Ecuador and Venezuela (Martinez, 2017).

Additional information on municipal characteristics is provided by CEDE at Universidad de los Andes.[14] CEDE collects data from multiple sources, mostly government agencies. Appendix Table A2 provides summary statistics of predetermined characteristics (i.e., measured before the start of our sample period), disaggregated by FARC exposure. 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. We discuss below how we incorporate these differences into our research design.

3.2 Research Design

We estimate the effect of conflict on investment using a Difference-in-Difference (DiD) strategy that compares municipalities with varying historical FARC exposure, before and after the peace agreement. All our regressions include municipality and department-month fixed-

government against FARC after 2002, as well as the demobilization of right-wing paramilitary groups between 2003 and 2006.

[14]In Appendix B we describe in detail the main data sets and variables that we use in the paper.

effects. The former control for all persistent differences across municipalities that may affect demand for credit (e.g., geographic characteristics). The latter account for time-varying factors that simultaneously affect all municipalities in the country (e.g., macroeconomic conditions), as well as for those that are department-specific (e.g., regional weather shocks).[15]

Our identifying assumption is that in the absence of the peace agreement we should not observe any differential change in the demand for credit in FARC municipalities. Importantly, the peace deal was the culmination of a multi-year negotiation process, which was associated with a gradual reduction in hostilities. While our main focus of interest is the period following the definitive peace agreement in November 2016, some events before that date could have plausibly affected producers' investment decisions. In particular, the Victims Bill from June 2011, the announcement of the start of peace talks in September 2012, or the partial agreement over specific items on the negotiation agenda may have led producers 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, extending from January 2009 to May 2011, is a pure *pre-period* that covers the end of the Uribe government 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 renewed attitude towards the conflict by signing the Victims Bill, to October 2016. The third period (which we call *agreement*) starts in November 2016, when the final agreement was signed and ratified, and runs until the end of the sample in December 2019. As part of our robustness checks, we verify below that the results are robust to alternative partitions of the sample period.

We use the following specification to capture changes in our outcomes of interest in FARC municipalities during either the negotiations or agreement stages:

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

where $y_{i,j,t}$ is an outcome of interest in municipality i located in department j in month t. α_i and $\delta_{j,t}$ 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 predetermined FARC exposure with the time dummies for the negotiation and agreement periods. The effect of the individual terms in these interactions is absorbed by the included set of fixed effects. Our coefficients of interest are β_1 and β_2, which capture the change in FARC municipalities during the corresponding period, relative to the pre-period. $\epsilon_{i,j,t}$ is an error term that we cluster two-

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

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, and between municipalities in the same department within the same year (i.e., at a higher temporal level than our monthly unit of observation). The latter flexibly accounts for spatial correlation within departments.

$X_{i,t}$ is a set of time-varying controls that we introduce to account for potential confounders. As mentioned above, FARC municipalities exhibit significant cross-sectional differences in several predetermined covariates (Cols 1-3 in Appendix Table A2). Per se, these differences do not invalidate our DiD design, which relies on the assumption that any effect of these differences is stable, rather than nonexistent. However, the time-varying effects of these covariates could potentially bias our estimates. For instance, changes in the price of agricultural products or in policies concerning international trade or narcotics could differentially affect the demand for credit in FARC municipalities (e.g., Prem et al., 2021). In our preferred specification, we address this concern by including as additional controls month fixed effects interacted with: (i) dummies for quartiles of the rural share of the 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.[16]

Our set of baseline controls captures some of the most intuitive sources of variation in the demand for credit in rural areas. As an alternative approach, we use a LASSO regression (Belloni et al., 2014) to select the optimal controls that best predict FARC exposure and we replicate the analysis including month fixed effects interacted with each of them.[17] As yet another way of addressing imbalance in predetermined covariates, we estimate a propensity-score weighted regression following Hirano and Imbens (2001).[18]

The high frequency of the data enables us to also estimate a more flexible *event study*

[16]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.

[17]Appendix Table A2 shows the covariates chosen by the LASSO regression.

[18]This procedure improves balance by restricting the sample to the common support of the propensity score for FARC exposure and by weighting observations corresponding to non-FARC municipalities by the inverse of a non-parametric function of the propensity score. Hirano et al. (2003) show that this weighting scheme improves efficiency. Appendix Table A2 shows the first-stage Probit regression used to estimate the propensity scores, while Appendix Figure A3 shows the distribution of propensity scores disaggregated by FARC exposure. The common support ranges from 0.05 to 0.75 and includes 757 municipalities. Appendix Table A3 shows that propensity score weights improve balance in predetermined covariates, with only one significant difference at the 10% level (out of 23 covariates) between FARC and non-FARC municipalities.

specification that captures monthly changes in the outcome in FARC municipalities:

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

where τ_t is a dummy equal to one for month τ. The coefficient γ_t captures the change in the outcome in FARC municipalities 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. While the parallel trends assumption underlying our DiD design is essentially untestable, we use the event study specification to check for *pre-trends* in our outcomes of interest. This specification also allows us to better understand the dynamics of the effects.

4 Main Results

We begin this section by providing first-stage estimates of the change in conflict intensity in FARC municipalities during the negotiations and agreement phases. We then present our main results on the effect of conflict on credit applications and disbursed loans. At the end, we discuss our battery of robustness tests and we examine heterogeneous effects.

4.1 Conflict Intensity

Figure 1 shows estimates from a year-level version of equation 2 using the conflict index based on UARIV data as the dependent variable. Conflict intensity starts to decline in FARC municipalities after the start of peace negotiations in 2012, with the difference relative to 2009 becoming statistically significant after 2014.[19] This reduction in violence then stabilizes at about 0.3 standard deviations below the mean after the final agreement in 2016. Appendix Table A4 provides estimates of equation 1 for the conflict index, as well as for the 12 conflict measures that we use to construct it. The results show that FARC municipalities experience a significant reduction in conflict intensity both during the negotiations and the agreement periods, which is mostly driven by fewer incidents of forced displacement, homicides, kidnappings, and accidents involving land mines. Hence, if the contemporaneous level of violence is the main mechanism through which conflict affects investment, we should observe higher demand for credit in both the negotiation and agreement periods.

[19] FARC continued to pose a meaningful security threat after the start of peace negotiations in September 2012. On average, there were 135 yearly conflict events involving FARC between 2010 and 2014. For example, a FARC ambush in Arauca department caused the death of 15 soldiers in July 2013 (BBC News, 2013).

4.2 Loan Applications and Disbursed Credit

Table 1 presents our main results. Columns 1-5 show estimates of equation 1 using the monthly number of loan applications per 10,000 inhabitants as the dependent variable. All columns include municipality and department-month fixed effects. Column 1 shows results from a parsimonious specification with $\text{FARC}_i \times \text{Agreement}_t$ as the only regressor of interest and no additional controls. The estimate for β_2 indicates that FARC municipalities experience a 2.3 unit increase in the loan application rate after the final peace agreement. This is a precisely estimated and sizable effect, equivalent to 13% of the sample mean.

We verify that the previous result is not driven by time-varying effects of predetermined characteristics that correlate with FARC exposure and may affect producers' willingness to invest. In column 2, we include as additional controls month fixed effects interacted with the predetermined covariates listed in section 3.2 above. The inclusion of these controls leads only to a slight reduction in $\hat{\beta}_2$, which remains positive and statistically significant.

Column 3 shows results from our preferred specification including $\text{FARC}_i \times \text{Negotiation}_t$ as an additional regressor (i.e., disaggregating the period before the agreement). 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 relative to column 2 and becomes very similar to the initial estimate in column 1. The difference between $\hat{\beta}_1$ and $\hat{\beta}_2$ is statistically significant at the 0.1% level. Figure 2 shows the corresponding estimates of equation 2, our event-study specification. As suggested by the previous results, 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 increase sharply after the final peace agreement.[20] These results show that the higher demand for credit only materializes after the final peace agreement is signed, despite a decrease in violence during the negotiations phase. This suggests that reductions in conflict intensity do not affect willingness to invest as long as uncertainty about renewed violence remains, in line with previous findings by Besley and Mueller (2012) on the impact of urban terrorism on house prices in Northern Ireland.

Columns 4 and 5 provide additional evidence against the potentially confounding effect of imbalance in predetermined covariates. In column 4 we use a LASSO regression to determine the optimal set of predictors for FARC exposure (Belloni et al., 2014), which we then interact with month fixed effects and include as additional controls. Alternatively, in column 5 we replicate the analysis using propensity score weights (Hirano and Imbens, 2001). The results

[20] 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 A4 provides an alternative visualization at the quarter level, while Table A5 provides estimates of equation 1 at this higher level of temporal aggregation.

look very similar in both cases to the ones from our preferred specification in column 3.[21]

In columns 6-7 we turn our attention to the amount of credit disbursed. The dependent variable in column 6 is the number of disbursed loans, while in column 7 it is the total amount of credit disbursed (in millions of 2019 COP). Both outcomes are normalized by population in 2008, similarly to the loan application rate in columns 1-5. Column 6 shows a small and insignificant increase in disbursed loans during the negotiation phase, but a 2.1 unit increase 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 80% of the observed increase in loan applications, which is very similar to the average approval rate in the sample of 78%.[22] Column 7 shows that *monthly* BAC disbursements in FARC municipalities increase by 19.1 million COP per 10,000 inhabitants after the end of the conflict. This is equivalent to a 16.7% increase over the sample mean. Based on the nominal exchange rate, this amounts to 122,000 USD in extra credit to small producers in the average FARC municipality every year, while the PPP-adjusted exchange rate suggests a yearly increase close to 280,000 USD. These results point to a sizable positive impact of peace on the local economy in FARC municipalities.

4.3 Robustness Checks

In this section, we show that our main result concerning higher investment in FARC municipalities after the peace agreement is robust to a battery of sensitivity tests. We summarize these tests below and leave figures and tables for the online appendix. For these tests, we focus on our preferred specification corresponding to column 3 of Table 1.

Figure A5 replicates the analysis for different values of the threshold percentile of the distribution of total FARC events (1996-2008) that we use to define conflict exposure. Our baseline measure corresponds to the top quartile. We consider threshold values between the 31st percentile (i.e., the extensive margin) and the 95th percentile. The estimate of β_2 remains positive and significant throughout, while the estimate of β_1 is always smaller and mostly insignificant. Reassuringly, the estimate of β_2 increases with the value of the threshold, consistent with the idea that the impact of the peace agreement on producers' willingness to invest is larger in municipalities with higher exposure to FARC violence.

As further evidence of robustness regarding the measure of FARC exposure, Table A5 shows that the results are unaffected if we replace our binary measure with the continuous measure of aggregate FARC attacks. This table also shows that the results are similar if we

[21]For the analysis in columns 4-5, we focus on predetermined characteristics with available information for all municipalities. Appendix Table A6 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 for some municipalities.

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

measure FARC activity using data from an alternative source (i.e., CEDE at Universidad de los Andes). We show in Figure A6 that the results are also robust to using shorter time windows to measure FARC exposure (i.e., closer to the start of the sample period).

Regarding our partition of the sample period, 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). We show below that our main result is also robust to restricting the sample period to President Santos' second term in office (i.e., keeping fixed the party in power at the national level), as well as to changes in the end date of the sample period. To ensure that the results are not driven by events in a specific region, we replicate the analysis excluding one department at a time in Figure A7.

We also consider additional controls. While our baseline analysis accounts for scale effects by normalizing all outcomes by population, we further show in Table A5 that the results are robust to expanding our set of controls to include month fixed effects interacted with dummies for quartiles of population in 2008. We also show that the results are robust to the inclusion of month fixed effects interacted with dummies for each of seven different municipal categories. These categories are formula-determined as a function of population and municipal revenue. They affect various aspects of local governance, including the institutional complexity of the municipal government and the remuneration of elected officials.

4.4 Heterogeneous Effects

In this section, we examine potential heterogeneity in the effect of peace on the demand for credit in FARC municipalities. We focus on heterogeneous effects based on proximity to markets, levels of development, and the demand for land restitution in the context of the Victims Bill of 2011. For each variable, we divide the set of FARC municipalities into two equally-sized groups (i.e., above and below the median). 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 these variables so that larger values (i.e., high) correspond to more desirable attributes. Table 2 shows the results. The dependent variable in all regressions is the loan application rate.

The first 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 peace is much larger in FARC municipalities with high market access (β_2^{high}). This effect is significantly different from the estimate for FARC municipalities with low market access (β_2^{low}), which is small and insignificant. For instance, the estimates in column 1 show that FARC municipalities in close proximity to wholesale markets experience a 25% increase in the demand for credit (relative to the sample mean) after the peace deal. These heterogeneous effects strongly suggest that conflict is not the binding constraint on investment in remote and poorly connected areas, in line with a growing literature on the welfare gains from market integration (Donaldson, 2015). These results also have immediate policy implications, namely that post-conflict policies should prioritize ensuring adequate access to markets for conflict-affected areas in order to fully reap the economic dividends of peace.

Column 4 examines heterogeneous impacts based on the share of the population classified as non-poor according to the index of unmet basic needs (UBN) in the 2005 census. Municipalities with higher shares of non-poor arguably have higher incomes and better public goods. We find that the effect of the peace agreement is higher in these municipalities, but the difference between β_2^{high} and β_2^{low} is smaller than in the previous columns and is not statistically significant (p=0.22). This suggests that the previous heterogeneous effects based on market access are not simply picking up heterogeneity based on the level of development.[23] At the same time, the results in column 4 provide suggestive evidence that the investment boom caused by the peace deal is larger in municipalities that were already better off, which could aggravate regional inequality. In this regard, Appendix Figure A8 shows that the increase in credit demand in FARC municipalities is concentrated in the Andean and Eastern regions, while there is no effect in the Caribbean, Pacific, or Amazon regions. The latter regions have been traditionally much poorer.

Finally, column 5 examines the potential complementarity between peace and access to land, based on the total number of applications for land restitution (per 10,000 inh.) submitted as part of the implementation of the Victims Bill between 2011 and 2019. We find that FARC municipalities with more applications for land restitution experience a larger increase in the demand for credit, though the difference between β_2^{high} and β_2^{low} is not statistically significant (p=0.19). These results provide suggestive evidence of a complementarity between peace and access to land, but also indicate that our main findings are not driven by the land restitution policy ($\hat{\beta}_2^{\text{low}}$ falls just short of statistical significance, p=0.104). Moreover, these results should be interpreted with caution as applications for land restitution are measured during the sample period and are plausibly affected by the end of the conflict.

[23] Appendix Table A7 shows the cross-sectional correlation of the sources of heterogeneity that we consider. Most correlations run in the expected direction (e.g., municipalities closer to Bogotá have higher shares of non-poor). However, these correlations are moderate for the most part (i.e., smaller than 0.4 in absolute value), suggesting that these variables do not have the same information content.

5 Mechanisms

In this section, we study the mechanisms through which peace leads to higher investment. We first introduce a simple formal model to analyze producers' investment decisions. Despite being highly stylized, the model helps us to characterize different ways in which conflict may affect investment and guides our empirical analysis of mechanisms. We consider several different explanations for our results, including changes in supply-side factors, in features of investment projects (i.e., risk, returns), or in characteristics of producers (i.e., risk aversion, wealth, collateral). Ultimately, the evidence suggests that greater project returns (i.e., higher payoff if project succeeds) play a more prominent role than changes in other factors.

5.1 A Simple Model of Investment

Suppose that a producer 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 producer 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 producer has exogenous wealth $w_0 > 0$. We assume that initial wealth is either too low or insufficiently liquid, such that the producer 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 ($a > 0$). We refer to $b(l, i, a)$ as the total cost of investment. For simplicity, we assume that the producer fully pays back the loan if the project succeeds and defaults on the loan if the project fails, in which case she pays a cost given by $k > 0$.[24] This cost may reflect lost wealth pledged as collateral, additional payments from the ensuing collection process, and the reputational cost incurred from defaulting on the loan (e.g., lower credit score). If the producer invests, her expected utility is:

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

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

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

[24] Our results are qualitatively similar as long as the probability of default is higher if the project fails.

By equating payoffs, we obtain the following indifference condition:

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

Equation 3 provides straightforward comparative statics on the factors that affect the investment decision. All else equal, the producer is more likely to invest in projects with a higher return (r) or lower risk (i.e., higher probability of success q). She is less likely to invest as the total cost of investment (b) or the loss from a failed project (k) increase. A producer with higher risk aversion (ρ) is 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. Finally, the effect of changes in collateral (i.e., improved property rights over wealth) is theoretically ambiguous. Higher collateral can reduce the cost of investment (b), but also implies a larger loss if the project fails (i.e., higher k).

Equation 3 characterizes the investment decision of a single producer. We can easily extend the model to accommodate multiple producers by including a source of heterogeneity that determines which of them invest in equilibrium. For this purpose, it is useful to distinguish between elements in the model that are fixed parameters and those that potentially correspond to random variables (which could vary across individuals, investment projects, or municipalities). For example, we can think of the interest rate (i) as roughly constant in our setting.[25] The introduction of a random variable gives rise to a threshold condition that determines the investment decision as a function of the fixed parameters. For instance, if investment opportunities randomly vary in their return (r), those with a sufficiently low return are the ones that will fail to materialize. We further discuss this specific version of the model in section 5.5 below. As we explore the different potential mechanisms below, we try to distinguish between *treatment* effects (i.e., how conflict changes the investment decision) and *selection* effects (i.e., which producers or projects are forgone due to conflict).

5.2 Supply-Side Factors

There are several intuitive explanations for our findings that relate to changes in supply-side factors after the conflict ends. To start, it seems plausible that conflict hindered BAC operations in FARC municipalities. For example, conflict could make BAC branches more costly to operate or could make it difficult to send field officers to promote BAC's products. This would increase the cost of applying for a loan (a). Alternatively, the end of conflict

[25] As discussed in section 2.2, most BAC loans use rediscounted funds from FINAGRO. Implicitly, we assume an almost perfectly elastic supply of loans by BAC based on the abundant availability of FINAGRO funding and the restrictions that FINAGRO imposes on interest rates. BAC's almost full control over the credit market for small producers further allows us to abstract away from general equilibrium considerations.

could have led to changes in BAC policies that affect the cost of investment. For instance, BAC may have been reluctant to lend money in FARC municipalities before the peace deal due to limitations in its monitoring ability (i.e., moral hazard). It is also possible that the national government may have increased the supply of credit in FARC municipalities as a way to fulfill its commitment under the peace agreement to promote economic development in rural areas. Such policies could be reflected in higher loan approval rates or lower interest rates. Any of these changes would correspond to a lower total cost of investment (b).

Table 3 provides evidence on these potential channels. The dependent variable in columns 1-2 is the loan application rate. In column 1 we expand our preferred specification (i.e., column 3 of Table 1) to also include an indicator for BAC branch presence. In column 2 we control instead for the distance to the closest branch. As expected, having a BAC branch in the municipality is associated with a higher application rate, while a greater distance to the nearest branch has the opposite effect. However, our estimates of β_1 and β_2 hardly change when we control for these factors relative to our baseline results in Table 1.

Columns 3-7 study changes in other dimensions of BAC policy. 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 producers in remote areas to offer the bank's products. In column 4, the dependent variable is the loan approval rate.[26] Both estimates of β_2 are small and insignificant, suggesting no meaningful change after the conflict ends. In column 5, we replicate the analysis on loan approvals at the application level. This level of disaggregation enables us to condition on detailed characteristics of the application.[27] The dependent variable is a dummy equal to one if the application was approved. The results show that the peace agreement does not lead to changes in approval rates in FARC municipalities, even after accounting for potential changes in applicant characteristics.

Back to the municipality-month unit of observation, the dependent variable in column 6 is the share of loans that use FINAGRO funding, while in column 7 it is the average interest rate. As mentioned above, most BAC loans (67%) use rediscount resources from second-tier bank FINAGRO. These loans are exclusively for agriculture and have a subsidized interest rate. It is possible that the government increased the supply of credit in FARC municipalities

[26] The sample size is smaller in columns 3-4 (7) due to municipality-months without any applications (disbursements). Additionally, data on BAC field officers is only available until December 2017. Appendix Figure A9 shows that our main results are robust to changes in the final month of the sample period.

[27] We control for applicant's gender, intended loan use, credit line, and regional headquarter where the loan originates, as well as for the score awarded by the credit bureau at the initial stage and the credit score from BAC's own scoring models. Appendix Figure A10 shows the corresponding event study plot. We obtain similar results if we control for all available variables in BAC's data (assets, income, experience, plot size, education) or if we include loan analyst fixed effects (estimates not reported). Data from BAC's scoring models is only available after July 2012, so we are unable to study the effect of the negotiations period.

after the peace deal by facilitating more funding from FINAGRO or by further subsidizing interest rates. However, we find no evidence of change in either of these outcomes.

In column 8, 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, such as changes in personnel in branches that mostly serve FARC municipalities, 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 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, which is highly comparable to the effect size that we observe at the municipality level. The estimate of β_1 is less than half as large and the difference between $\hat{\beta}_1$ and $\hat{\beta}_2$ is statistically significant at the 0.1% level.

Columns 9 and 10 look more closely 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 post-conflict development policy was the assignment of 16 different areas (comprising 170 municipalities) for inclusion in Regional Development Programs (*Planes de Desarrollo con Enfoque Territorial, PDET).* In column 9, we include month fixed effects interacted with separate dummies for each of these areas and fail to observe any meaningful change in our estimates of β_1 and β_2. This suggests that neither the actual implementation of PDETs nor producers' expectations of greater public investment in these areas are driving our results.[28] Alternatively, in column 10 we restrict the sample period to coincide with the second term of the Santos administration, shutting down potentially confounding effects from other policies that differentially target FARC municipalities by previous or later governments.[29] The results are once again unchanged.

Taken together, the previous evidence shows that the increase in investment in FARC municipalities after the peace agreement is not driven by changes in supply-side factors. In terms of our model, the end of the conflict does not change the total cost of investment (b).

5.3 Risk and Loan Performance

Another plausible explanation for our findings is that conflict increases the level of risk associated with an investment project. This is captured in our model by the probability of failure

[28]Appendix Table A8 shows that the increase in loan applications after peace is higher in FARC municipalities not included in PDETs. The effect is also concentrated in FARC municipalities that did not house the camps in which FARC cadres initially grouped during demobilization.

[29]Santos' second term includes 27 months before the final peace agreement and 21 months afterward.

$(1-q)$. Changes in risk could be related to extortion if FARC presence is unpredictable and this group behaves like a *roving bandit*, with a short time horizon and a high expropriation rate (Olson, 1993).[30] In this case, project success would require the realization of an additional event corresponding to FARC not plundering the municipality. Alternatively, risk may also increase if unpredictable events such as acts of terrorism or direct combat between insurgents and government forces lead to the destruction of the object of investment (e.g., ruined fields). In any of these cases, conflict increases the probability of project failure and leads to lower investment. In this section, we shed light on these mechanisms by studying the effect of the peace agreement on several measures of risk and loan performance. To the extent that the probability of default is higher when investment fails, these outcomes can help us to establish whether peace reduces project risk (i.e., the probability $1-q$).

Table 4 presents the results. The dependent variable in column 1 is the average credit score of loan applicants.[31] We find no change in the average ex-ante risk of loan applicants in FARC municipalities after the peace agreement. Column 2 exploits a unique feature of our setting, which is that FINAGRO requires BAC to audit the investment sites of some of the recipients of loans issued with its funding. These visits provide first-hand information on the potential misuse of funds.[32] On average, 14% of audits reveal some irregularity, ranging from inconsistencies in values or quantities to the complete absence of the investment or inability to produce receipts. Audit reports usually include scanned receipts and photographic records of the investment, which reduces the risk of collusion. The results show that the share of visits with irregularities also remains unchanged in FARC municipalities after the agreement. This constitutes evidence of an increase in actual physical investment after peace.

We turn next to delinquency rates. We focus initially on new loans disbursed each month and calculate the share that goes 60 days past due at any point in the future. This measure can easily be confounded by compositional effects, as loans disbursed in earlier sample months are observed over a longer time period and mechanically 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 to ensure 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

[30] Former FARC hostages report long treks through the jungle, often unanticipated, during which insurgents raided local farms for supplies (Gonsalves et al., 2009; Betancourt, 2011).

[31] As discussed in section 2.2 all applications go through an initial check with a credit bureau, which provides a report including a credit score. Applicants lacking a credit history are fast-tracked for review by a loan officer. Appendix Table A9 shows that the share of applications with a credit score (87% on average) does not change after the peace agreement. This information is only available since July 2012.

[32] Information from these audits is only available since July 2011. Appendix Table A9 shows that the share of audited loans in FARC municipalities increases marginally after the peace agreement, which is consistent with a slight improvement in BAC's monitoring ability.

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 for new loans. Figure 3 shows the event study plot (i.e., equation 2) using 60-day default over a two-year horizon as the 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. 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 could be coming from riskier projects that become profitable enough after the peace deal, which would lead to a counteracting increase in the average default rate. In column 5, we shut down the selection effect by focusing on the share of outstanding loans per municipality-month that are 60 days past due. This is also a commonly used measure of delinquency in bank portfolios. Still, the estimates remain small and insignificant, further suggesting no change in risk.[33]

The previous results suggest that there is no meaningful link between conflict and project risk in our setting. We find no evidence that the peace agreement affects the probability of default among outstanding loans. Furthermore, new loans issued in FARC municipalities after the agreement have a similar level of risk, as measured by ex-ante credit scores, in-person audits, and loan performance. We conclude that changes in risk are not driving the higher demand for credit. These results also suggest that a public bank like BAC can accommodate a large increase in the demand for credit originating from areas affected by conflict without experiencing a deterioration in the quality of its portfolio.

5.4 Risk Aversion, Wealth, and Collateral

The effect of conflict on investment could also be mediated by changes in the individual characteristics of loan applicants. In this section, we focus our attention on three applicant characteristics considered in our model: risk aversion, wealth, and collateral. Our model predicts a higher willingness to invest for producers with lower risk aversion (ρ) or higher initial wealth (w_0). The effect of higher available collateral is theoretically ambiguous, as this can reduce the cost of the loan (b), but also increases the loss to the producer if the project fails (k). At this point, the distinction between treatment and selection effects is also relevant. For instance, peace may increase investment by reducing producers' level of risk aversion (i.e., treatment). But peace could also induce more risk averse producers to invest (i.e., selection), even if the effect operates through an alternative channel, such as returns.

Risk Aversion: If conflict makes producers more risk-averse, then our model suggests

[33]Appendix Table A9 shows that the results on delinquency are very similar if we use other default thresholds or an alternative measure based on extended payments after the original loan term.

that the peace agreement could lead to an increase in investment, in line with our main results. The relationship between conflict and risk aversion has occupied a growing empirical literature, but the findings remain somewhat inconclusive.[34] Moreover, previous studies have largely focused on increased exposure to conflict and little is known about the effects of peace (i.e., whether the effect is symmetric). Unfortunately, data on risk aversion is not readily available for BAC loan applicants. We thus take an alternative approach and focus on observable characteristics of applicants that plausibly reflect differences in risk aversion. In this regard, previous work suggests that risk aversion is higher among women (Charness and Gneezy, 2012), as well as among older (Dohmen et al., 2017) or more educated individuals (Jung, 2015). If the peace deal makes investing more attractive for individuals who are more risk-averse (i.e., selection effect), we should observe a growing share of individuals in the applicant pool with characteristics that correlate positively with risk aversion.

We study applicant characteristics in Table 5. The dependent variable in column 1 is the share of loan applications submitted by new BAC clients.[35] This share increases by 2.4 percentage points (pp) in FARC municipalities after the peace agreement (6% increase over the sample mean). This result shows that individuals that previously were not demanding credit at all are now willing to do so. It suggests that peace has a positive effect on financial inclusion, which is associated with higher long-run growth (Levine, 2005). Columns 2 and 3 then show small and insignificant changes in the share of women and in the average applicant age. Hence, the new applicants are not systematically different in terms of gender or age. In column 4 we find 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 (Jung, 2015), which causes them to forgo investing under conflict.[36]

Wealth: Our assumed CRRA utility function implies that producers with higher wealth (w_0) are more willing to pursue a risky investment. If wealth is directly affected by conflict, then the average assets of loan applicants should increase in FARC municipalities after the peace deal. However, the rapid increase in the demand for credit after the peace deal suggests that this is not the main driver of our results (i.e., Figure 2). Alternatively, if conflict reduces investment through some other channel, the average applicant wealth could fall because poorer individuals now find investing sufficiently attractive (i.e., selection).

Column 5 in Table 5 shows that average applicant assets decrease by 1.4 million COP

[34]While Moya (2018), Brown et al. (2019), and Jakiela and Ozier (2019) find a positive relation in Colombia, Mexico, and Kenya respectively, Callen et al. (2014) fail to find any relation in Afghanistan and Voors et al. (2012) find a negative one in Burundi.

[35]We create this variable using data on loan applications dating back to 2005. Results are similar if we only use data after 2009 or if we define new clients based on disbursements (not reported).

[36]Though conflict has direct negative effects on human capital (e.g., Namen et al., 2021), this mechanism is unlikely to affect investment over the relatively short time horizon that we are studying.

(roughly USD 500) in FARC municipalities after the agreement, equivalent to a 2.3% decrease relative to the sample mean. This result is consistent with less wealthy individuals becoming more willing to invest after peace. It suggests that the peace agreement is a progressive policy that disproportionately benefits somewhat poorer individuals. The estimate for average income in column 6 is also negative, albeit small and insignificant. These results indicate that higher investment after peace is not predominantly due to changes in wealth or income.

Collateral: Lack of collateral is one of the main explanations for credit rationing in rural settings (Bardhan and Udry, 1999). In our model, higher collateral has two offsetting effects on producers' willingness to invest. On the one hand, more collateral reduces the cost of applying for a loan (a) and makes investing more attractive. For instance, applicants in our setting that do not use the special loan guarantees provided by the government (e.g., FAG) can forgo the associated yearly fees. On the other hand, more collateral means a larger loss in the event that the project fails (i.e., higher k). The net effect is thus undetermined.[37]

While increases in wealth often coincide with higher collateral, in settings like ours this relationship can be thwarted by weak property rights (Besley and Ghatak, 2010). BAC officials report anecdotally that loan applicants often struggle to secure valid supporting documentation for their alleged collateral. In this regard, the land restitution policy put in place by the central government as part of the implementation of the Victims Bill in 2011 could be an important mechanism behind our results. As part of this policy, the government restitutes land ownership to victims that were forcibly dispossessed and provides them with a property title. The results on heterogeneous effects in Table 2 show that the increase in loan applications after the peace deal is higher in municipalities with more claims for land restitution, though the difference with municipalities with fewer claims is not statistically significant. This suggests a complementarity between peace and access to land.

In column 1 of Table 6 we provide additional evidence by studying the share of loans with a government guarantee. This share decreases by 2.7 pp in FARC municipalities after the peace agreement, a drop equivalent to 3.6% of the sample mean. This result is consistent with the land restitution policy providing some producers with a land title that they can credibly use as collateral. However, it seems unlikely that an increase in collateral of this magnitude can fully explain our findings. The government agency in charge of supervising the land restitution process (*Unidad de Restitución de Tierras*) reports approximately 4,400 land restitution sentences between 2011 and 2020. A back-of-the-envelope calculation reveals that even if each of these translated into one additional loan, plus a spillover effect equally as large, this would still only explain less than one quarter of the observed increase in disbursed

[37]Boucher et al. (2008) provide a theoretical model formalizing the idea that the possibility of losing collateral when projects fail reduces the demand for loans, which they refer to as "risk rationing".

loans in FARC municipalities after the conflict ends.[38]

5.5 Project Returns

The remaining factor that can explain our findings corresponds to changes in project returns. In our model, a higher return (r) makes the investment more attractive, all else equal. Before the peace agreement, FARC presence could directly reduce the return on investment through regular extortion or taxation, which was a common practice by this insurgency (Arjona, 2016; Gilbert, 2022). Conflict could also indirectly reduce the return to investment through a reduction in local economic activity and aggregate demand, perhaps because of restrictions on business hours, mobility, or access to inputs (Amodio and Di Maio, 2017). Although direct measures of project returns are unavailable in our data, in this section we provide indirect evidence suggesting higher project returns after the conflict ends. For this purpose, we study the broader economic impact of the peace agreement using data on night-time lights, as well as the characteristics of disbursed loans. We also expand on the interpretation of our previous findings on heterogeneous effects based on market access.

Night Lights: It is plausible that the peace agreement leads to higher project returns through an aggregate demand mechanism. For example, a boom in local economic activity could increase the demand for agricultural products and drive up the returns of investment projects. Unfortunately, data on municipal GDP is not available for Colombia.[39] We can, however, use data on night-time lights (NTL) to proxy for local economic conditions (Henderson et al., 2012). In particular, the Day/Night Band (DNB) from the Visible Infrared Imaging Radiometer Suite (VIIRS) provides granular information on night-time luminosity at a monthly frequency since April 2012.[40] We aggregate the monthly VIIRS data on NTL 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. Our preferred measure collapses the data from its original monthly periodicity to quarterly averages in order to minimize the impact of measurement error, but we also provide results at the monthly level.

Figure 4 plots estimates of equation 2 at the quarterly level, using log NTL as dependent variable.[41] We observe a clear and stable increase in night-time luminosity in FARC mu-

[38]Column 6 of Table 1 shows an average monthly increase of 2.1 disbursed loans (per 10,000 inh.). There are 281 FARC municipalities in our sample and their average population is 16,000. Given that the agreement period has 38 months, the total increase in disbursed loans amounts to approximately 36,000.

[39]Our analysis of predetermined covariates in Appendix Table A2 includes an imputed value of yearly municipal GDP per capita from CEDE, which is only available for the period 2005-2009.

[40]The VIIRS sensor is mounted on the Suomi satellite launched in 2011. This sensor measures radiance over a large range and has onboard calibration, which ensures that data is comparable over time and across space. This represents a marked improvement over the widely used DMSP series (Gibson et al., 2021).

[41]Appendix Figure A11 shows the analogous figure at the monthly level.

nicipalities following the peace agreement. Appendix Table A10 provides the corresponding estimates of equation 1. On average, night lights increase by approximately 14% in FARC municipalities after the peace agreement. This sizable increase in NTL is consistent with a boom in local economic activity after the end of the conflict, which plausibly leads to higher returns to investment. Though some of this increase in NTL may be a reflection of investment projects funded with BAC loans, the quick timing of the effect suggests that this is not the main driver. Instead, the increase in NTL is plausibly capturing alternative channels through which the end of conflict impacts local economies, such as the loosening of restrictions on mobility or business hours, or lower extortion at the hands of armed groups.[42]

Market Access: Our previous findings on heterogeneous effects in section 4.4 show that peace does not lead to a meaningful increase in investment in areas far from markets. Our theoretical framework can accommodate these results if we assume that producers face random variation in project returns (i.e., r is a random variable with density f_r). This assumption yields a threshold condition such that producers invest if $r \geq r^\star$, which occurs with probability $1 - F_r(r^\star)$, where F_r denotes the CDF of r.[43] If the end of the conflict shifts this distribution to the right (i.e., peace directly increases returns, as suggested by higher NTL), then some projects that were deemed unprofitable under conflict will now have a high enough return to be pursued. Panel (a) in Appendix Figure A12 illustrates this result.

Suppose now that the actual return of the project is given by $R = mr$, where m stands for market access and is a positive constant taking two possible values: $m_{high} > m_{low} > 0$. Intuitively, higher market access leads to lower production and transportation costs and to higher payoffs in the event of project success. Under the assumption of stochastic returns to investment, the difference in market access will lead to different values of the indifference threshold $r^\star$. More specifically, the indifference threshold $r^\star_H$ corresponding to municipalities with high market access (i.e., $m = m_{high}$) will be lower than that of municipalities with low market access ($r^\star_L$), since $r^\star_H = r^\star/m_{high}$ and $r^\star_L = r^\star/m_{low}$. A lower threshold implies more investment, all else equal. If peace increases the return to investment (i.e., a rightward shift in the distribution of returns), the higher indifference threshold in FARC municipalities with low access to markets leads to a much smaller increase in investment. Panel (b) in Appendix Figure A12 provides a visualization of this result.

Loan characteristics: In Table 6 we provide further evidence of an increase in project

[42]Appendix Table A8 shows that our main result does not vary based on the presence of other armed groups, measured either before the start of the sample period or before the peace agreement.

[43]If we further assume that $k = w_0$ (i.e., producer loses all initial wealth if the project fails), then the indifference condition in equation 3 has a closed-form solution given by $r^\star = w_0(1/q^{1/1-\rho} - 1) + b$. The threshold $r^\star$ is increasing in b and ρ, and decreasing in q and w_0 (the latter for $\rho > 1$). Intuitively, producers need a higher realization of r in order to invest if the cost of investment is higher, they are more risk-averse, the probability of project success is lower, or they have lower wealth.

returns after the conflict ends, based on information on loan characteristics. We study the average loan size in column 2 and find no change. This suggests that the marginal projects pursued in FARC municipalities after the peace agreement are comparable in size to those that were previously pursued. In columns 3-5, we turn our attention to the maturity of loans. We find that the share of loans with a maturity of between 3 and 5 years decreases by 3.1 pp in FARC municipalities after the peace deal, while the share of loans with a maturity of 6 years or more increases by 2.8 pp (11% increase over the sample mean). 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. 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 peace leading to higher project returns, such that those projects that were previously deemed unprofitable due to their long maturity now become attractive enough.[44] In column 6, we look at the intended use of the loan. BAC classifies loans as providing funding for investment or working capital. In line with the higher average loan maturity, the results show a 3.5 pp increase in the share of loans required for investment purposes, which is equivalent to 5.4% of the sample mean.

In terms of the sectoral allocation of investment, in column 7 we find no change in the share of loans destined for agriculture (broadly defined).[45] Appendix Table A11 provides more disaggregate results for the 10 main products within agriculture. We find that the share of loans corresponding to fruit crops, cocoa, and pig farming increases in FARC municipalities after the peace agreement. Though some of these increases are large relative to the respective sample means, none of them exceeds 1.5 pp, suggesting that peace benefits a diverse set of rural producers. One agricultural product that is not in the BAC data is coca, the main input in the production of cocaine. Using data from the UN Office on Drugs and Crime, Appendix Figure A13 shows that the average share of land devoted to coca cultivation increases in FARC municipalities after 2015. This result is in line with findings by Prem et al. (2021) on the recent boom in narcotics production in Colombia. While the increase in local economic activity recorded by NTL could be partly driven by the illegal economy, the magnitude of the increase in coca cultivation is negligible (0.1 pp). Moreover, Appendix Table A8 shows

[44] More precisely, suppose that an additional feature of a project (besides b, q, and r) is its maturity, denoted by M. Assume that M and r are random variables with marginal densities f_r and f_M. M is also bounded above by $\bar{M}$. Each producer is faced with a random investment opportunity characterized by a pair (r, M), such that the actual return of the project is given by $R = r/M$. According to this expression, the actual return is lower if M is higher (keeping r fixed), which could happen if producers discount the future. In this case, the producer invests if $R > r^\star$ or $r > Mr^\star$. After the peace deal, a larger share of farmers with projects with the maximum maturity $\bar{M}$ will choose to invest since the probability of the event $(r, M) \in \{(r, M) : M = \bar{M}, r > \bar{M}r^\star\}$ is given by $\int_{\bar{M}r^\star}^{\infty} f_r(r)dr$, which increases if $f_r(r)$ shifts to the right.

[45] Appendix Table A8 shows no heterogeneity in our main results based on measures of soil quality.

that the increase in loan applications is comparable in FARC municipalities that have above or below median growth in coca cultivation between 2014 and 2018.[46]

6 Concluding Remarks

In this paper, we show that civil conflict leads small rural producers to forgo otherwise profitable investments. In our analysis, we use detailed microdata on the universe of loans from a large public bank in Colombia between 2009 and 2019. Our difference-in-difference strategy exploits the 2016 peace agreement between the Colombian government and insurgent group FARC, combined with pre-existing differences in FARC exposure across municipalities.

We find that business loan disbursements increase in FARC municipalities after the peace deal. This increase is driven by higher loan applications, with no change in supply-side factors. However, higher investment is only observed in FARC municipalities located close to markets and does not materialize before the peace deal is finalized, despite a large decline in violence during the preceding negotiations period. This suggests that uncertainty about future conflict matters more for investment decisions than the contemporaneous level of conflict. It also suggests that conflict is not the main binding constraint on investment in remote areas with weak market access. A simple theoretical framework combined with rich information on the characteristics of loan applicants and projects suggests that conflict hinders investment mostly by lowering project returns.

Though our research design is not meant to capture the macroeconomic effects of the peace agreement, our findings suggest a broadly positive economic impact. For instance, we show that night-time lights increase 14% in FARC municipalities after the conflict ends. Moreover, we find no change in delinquency rates or in misuse of funds, which suggests that the extra loans in FARC municipalities are funding profitable investments. We also see a higher share of new BAC clients among the pool of loan applicants, which indicates that peace contributes to financial inclusion. Our findings are somewhat mixed regarding the distributional effects of peace. On the one hand, the decrease in average applicant assets suggests that less wealthy individuals disproportionately benefit. On the other hand, the investment boom unleashed by the peace deal does not extend to some of the more remote and poorer parts of the country, such as the Pacific coast or the Amazon region.

[46] Results are similar if we classify FARC municipalities based on coca cultivation between 2000-2008 or 2000-2018 (estimates not reported).

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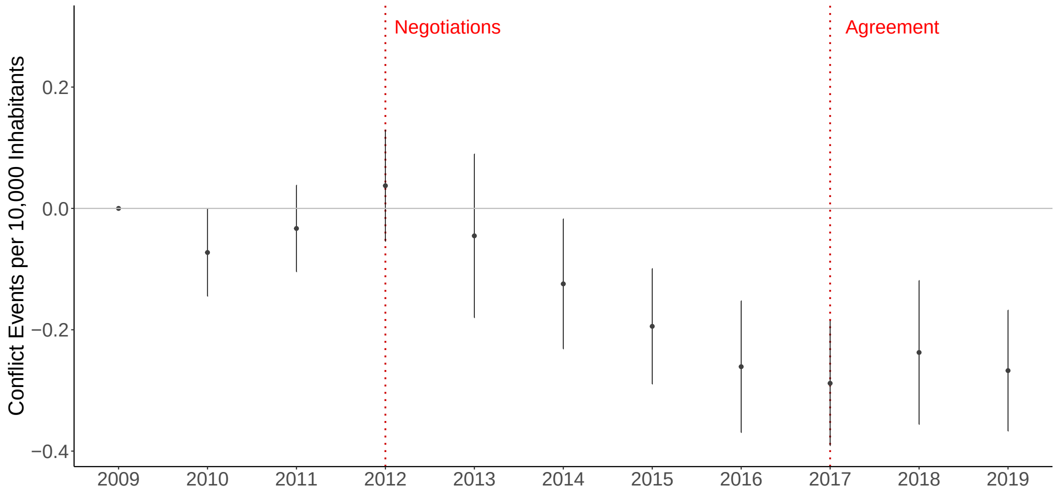
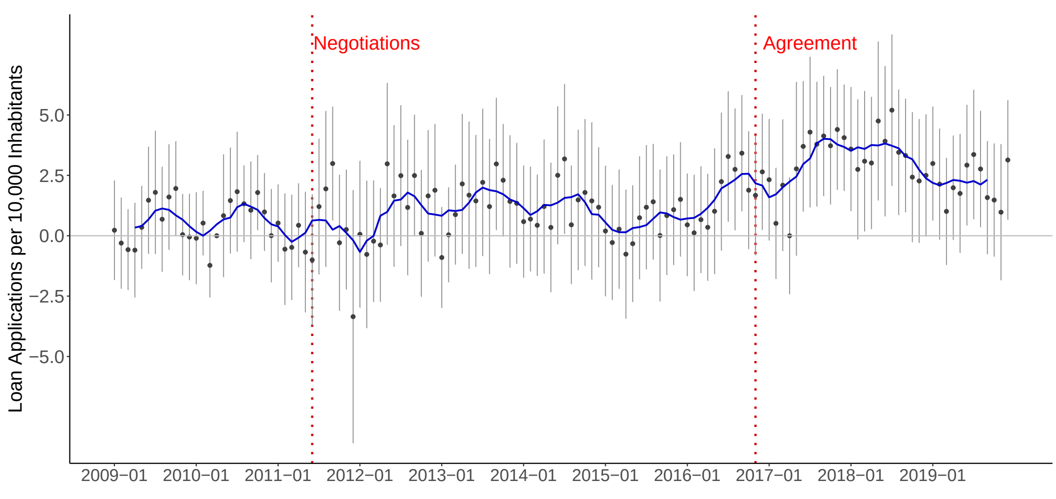
Figure 1: Conflict Intensity: Event Study



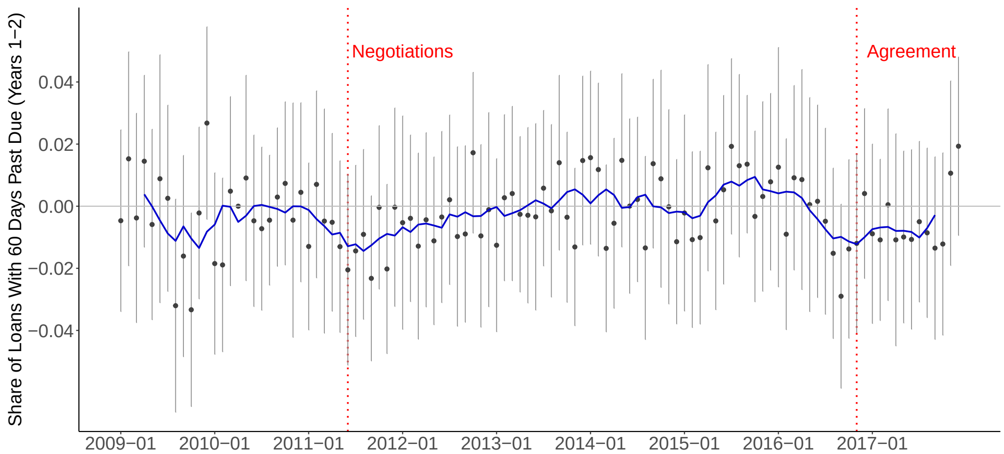
Notes: Figure shows point estimates and 95% confidence intervals from a regression of an aggregate conflict index (12 measures) on year dummies interacted with the indicator for FARC municipalities (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008). Unit of observation: Municipality-year. Regression includes municipality and department-year fixed effects, as well as year dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors clustered two-way by municipality and department-year.

Figure 2: Loan Applications: Event Study



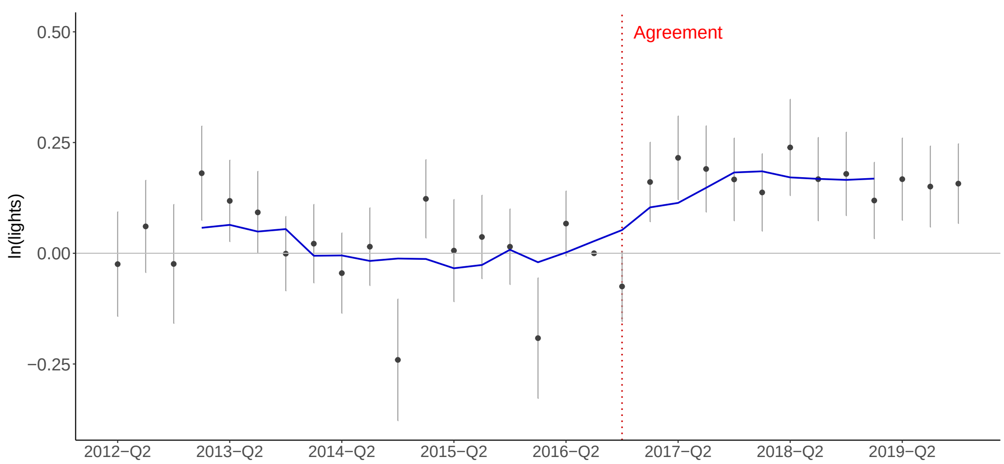
Notes: Figure shows point estimates and 95% confidence intervals from a regression of the number of loan applications (per 10,000 inhabitants) on month dummies interacted with an indicator for FARC municipalities (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008). Unit of observation: Municipality-month. Regression includes municipality and department-month fixed effects, as well as month dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The solid line depicts a centered six-month moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Figure 3: Delinquent Loans (60 days): Event Study



Notes: Figure shows point estimates and 95% confidence intervals from a regression of the share of disbursed loans that reach 60 days past due during their first two years on month dummies interacted with an indicator for FARC municipalities (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008). Sample period finishes in December 2017, but we track loans until December 2019. Unit of observation: Municipality-month. Regression includes municipality and department-month fixed effects, as well as month dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The solid line depicts a centered six-month moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Figure 4: Night-time Lights: Event Study



Notes: Figure shows point estimates and 95% confidence intervals from a regression of the log of night-time luminosity on quarter dummies interacted with an indicator for FARC municipalities (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008). Unit of observation: Municipality-quarter. The dependent variable corresponds to the average of the monthly area-weighted value per municipality, based on data from VIIRS. Regression includes municipality and department-quarter fixed effects, as well as quarter dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The solid line depicts a centered six-quarter moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Table 1: Loan Applications and Disbursements

	Application rate					Disbursement rate	
						Number	Value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{FARC}_i \times \text{Negotiations}_t$ [a]			0.567	0.905	1.066	0.701	7.611
			(0.643)	(0.624)	(0.775)	(0.489)	(4.639)
$\text{FARC}_i \times \text{Agreement}_t$ [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 × 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 dependent variable in columns 1-5 is the number of loan applications (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). Unit of observation: Municipality-month. 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 columns 2, 3, 5-7 are month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Column 4 includes month fixed effects interacted with predetermined 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: Heterogeneous Effects

	Dependent Variable: Loan Application Rate				
	Access to markets			Share Non-poor	Land Restitution
	Wholesale	Dpt. capital	Bogotá		
	(1)	(2)	(3)	(4)	(5)
$\text{FARC}_i \times \text{Negotiations}_t$ (Low) [a]	-1.451*	-0.979	-0.320	0.488	0.269
	(0.780)	(0.812)	(0.803)	(0.773)	(0.839)
$\text{FARC}_i \times \text{Negotiations}_t$ (High) [b]	2.361***	2.093**	1.375	0.643	0.946
	(0.906)	(0.860)	(0.944)	(0.915)	(0.820)
$\text{FARC}_i \times \text{Agreement}_t$ (Low) [c]	-0.189	0.698	0.936	1.549*	1.606
	(0.831)	(0.844)	(0.850)	(0.816)	(0.986)
$\text{FARC}_i \times \text{Agreement}_t$ (High) [d]	4.530***	3.899***	3.559***	3.040***	3.203***
	(1.100)	(1.054)	(1.095)	(1.078)	(0.910)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Department × Month FE	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Observations	148,104	148,104	148,104	148,104	148,104
R-Squared	0.708	0.708	0.708	0.708	0.708
Mean DV	17.963	17.963	17.963	20.612	17.963
p-value H_0: [c] = [d]	0.000	0.008	0.045	0.221	0.187
p-value H_0: [b] = [d]	0.002	0.01	0.001	0.000	0.001

Notes: The unit of observation is the municipality-month. In all columns, we divide FARC municipalities into two equally-sized groups (i.e., above/below median) based on the variable in the header. We rescale these variables such that higher values correspond to more desirable attributes. In columns 1-3, we use the distance in kilometers to the nearest wholesale market, to the departmental capital or to Bogotá. In column 4, we use the share of the population classified as non-poor based on the index of Unmet Basic Needs (UBN) in the 2005 census. In column 5, we use the total number of applications for land restitution per municipality between 2011 and 2019 (per 10,000 inh. in 2008). 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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: Loan Applications: Supply-Side Factors

	Application Rate		Share of Applications			Share FINAGRO	Interest Rate	Application Rate		
			Field	Approved						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\text{FARC}_i \times \text{Negotiations}_t$ [a]	0.581	0.569	-0.027*	0.011*		-0.004	0.071	0.071*	0.473	
	(0.641)	(0.640)	(0.015)	(0.007)		(0.013)	(0.348)	(0.042)	(0.666)	
$\text{FARC}_i \times \text{Agreement}_t$ [b]	2.397***	2.366***	0.020	-0.004	-0.001	-0.022	0.200	0.195***	2.274***	2.111***
	(0.740)	(0.738)	(0.018)	(0.007)	(0.004)	(0.016)	(0.425)	(0.050)	(0.786)	(0.535)
$\mathbb{1}(\text{BAC branch in muni.})_{i,t}$	5.472***									
	(1.047)									
Dist. to BAC branch $(\text{Km})_{i,t}$		-0.292***								
		(0.053)								
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Department × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Application-level controls	No	No	No	No	Yes	No	No	No	No	No
Municipality × Branch FE	No	No	No	No	No	No	No	Yes	No	No
Branch × Month FE	No	No	No	No	No	No	No	Yes	No	No
PDET × Month FE	No	No	No	No	No	No	No	No	Yes	No
Presidential terms	All	All	All	All	All	All	All	All	All	Santos II
Observations	148,104	148,104	110,648	136,055	1,176,743	133,576	133,576	2,172,547	148,104	53,856
R-Squared	0.708	0.708	0.641	0.305	0.101	0.710	0.654	0.783	0.713	0.790
Mean DV	17.963	17.963	0.323	0.778	0.82	0.716	11.807	1.225	17.963	18.818
p-value H_0: [a] = [b]	0.000	0.000	0.000	0.000	-	0.072	0.645	0.000	0.000	-

Notes: The unit of observation is municipality-month in all columns, except columns 5 (loan application) and 8 (municipality-branch-month). The dependent variable is listed in the column header. The application rate in columns 1-2 and 8-10 is the number of loan applications per 10,000 inhabitants. In column 3, the dependent variable is the share of applications generated by BAC field officers (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, while in column 5 it is a dummy equal to 1 if the loan is approved (data available since July 2012). The dependent variable in column 6 is the share of disbursed loans that use FINAGRO funding, while in column 7 it is the average interest rate among disbursed loans (expressed as percentage points above reference rate DTF). 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's centroid and the nearest BAC branch in kilometers. The sample in column 8 includes all municipality-branch combinations with non-zero loan applications at some point between 2009 and 2019. In column 9, we interact month fixed effects with separate dummies for each of the 16 sets of municipalities with Regional Development Programs (PDET). In column 10, the sample period is limited to Juan Manuel Santos' second term as president (Aug 2014 - Jul 2018). 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 in all columns except 3, 5 and 10. All regressions include department-month fixed effects. All columns also include municipality fixed effects, except column 8, which includes municipality-branch and branch-month fixed effects. Baseline controls in all columns include month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Column 5 includes the following application level controls: Applicant's gender, intended loan use, credit line, and regional headquarter where the loan originates, as well as for the score awarded by the credit bureau at the initial stage and the credit score from BAC's own scoring models. 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: Loan Outcomes

	Average Credit Score	Share of Audits w/ Irregularities	Share of Loans 60 Days Past Due		
			New loans		Outstanding Loans
			Year 1	Years 1-2	
	(1)	(2)	(3)	(4)	(5)
$\text{FARC}_i \times \text{Negotiations}_t$ [a]			0.002	0.001	0.003
			(0.002)	(0.004)	(0.005)
$\text{FARC}_i \times \text{Agreement}_t$ [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 × 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 is 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. 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. Data from BAC's scoring models is only available since July 2012 (column 1), while data on audits is only available since July 2011 (column 2). 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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: Characteristics of Loan Applicants

	All Applicants			Applicants in Scoring Models		
	Share New	Share Female	Average Age	Share w/ Secondary	Average Assets	Average Income
	(1)	(2)	(3)	(4)	(5)	(6)
$FARC_i$ 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
	(0.011)	(0.007)	(0.171)	(0.005)	(0.514)	(0.062)
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	136,055	136,055	136,055	82,562	82,562	82,562
R-Squared	0.324	0.313	0.289	0.438	0.498	0.531
Mean DV	0.376	0.414	44.436	0.388	58.857	3.988
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 1-3 is January 2009 to December 2019. The sample period in columns 4-6 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. $FARC_i$ 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 in all columns include month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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: Characteristics of Disbursed Loans

	Share Gvt. Guarantee	Average Size	Share w/ Maturity (Years)			Share w/ Intended Use	
			≤ 2	3-5	≥ 6	Investment	Agriculture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FARC_i x Negotiations_t [a]	0.002	-0.056	0.009	-0.005	-0.004	-0.003	0.001
	(0.012)	(0.120)	(0.012)	(0.010)	(0.011)	(0.010)	(0.011)
FARC_i x Agreement_t [b]	-0.027*	-0.080	0.004	-0.031**	0.028*	0.035**	-0.016
	(0.014)	(0.149)	(0.016)	(0.014)	(0.016)	(0.014)	(0.013)
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
Observations	133,576	133,576	133,576	133,576	133,576	133,576	136,055
R-Squared	0.636	0.481	0.556	0.485	0.562	0.558	0.657
Mean DV	0.750	7.863	0.371	0.368	0.261	0.65	0.769
p-value H_0: [a] = [b]	0.003	0.837	0.626	0.019	0.010	0.000	0.052

Notes: The unit of observation is the municipality-month. Observations lacking loan disbursements are excluded from the sample in all columns. The dependent variable is listed in the column header. Government guarantees in column 1 include FAG and FNG. The average amount disbursed in column 2 is measured in millions of 2019 COP. The complement to investment in column 6 is working capital. Agriculture in column 7 is broadly defined and includes cultivation of crops, livestock, fishing, and forestry. 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix (for online publication)

FORGONE INVESTMENT AMID CONFLICT: EVIDENCE FROM CREDIT MICRODATA IN COLOMBIA

Authors: Nicolás de Roux and Luis R. Martínez

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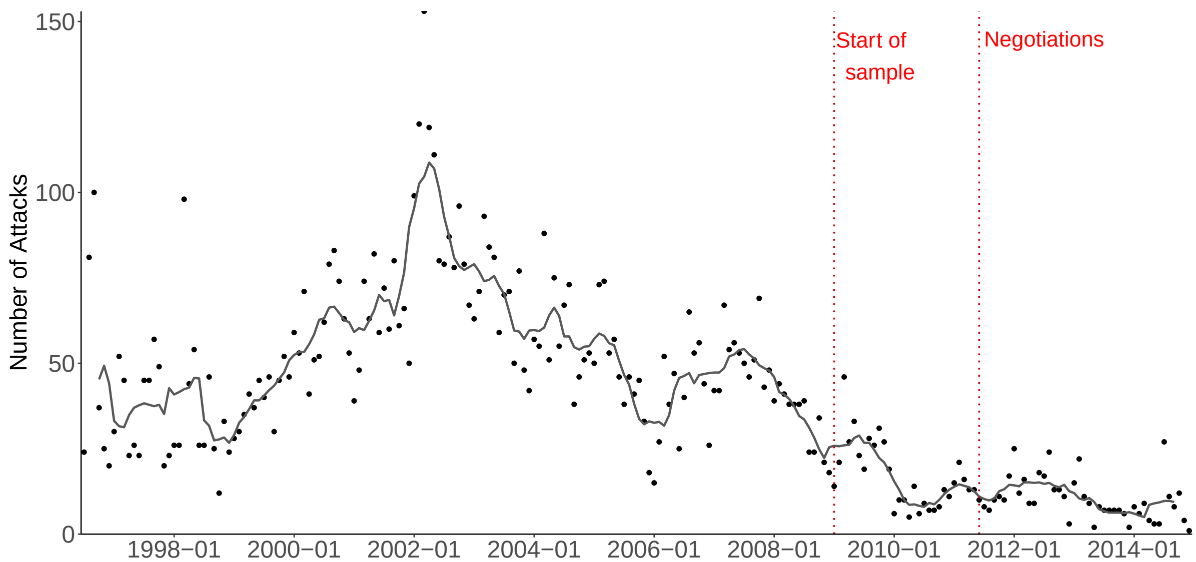
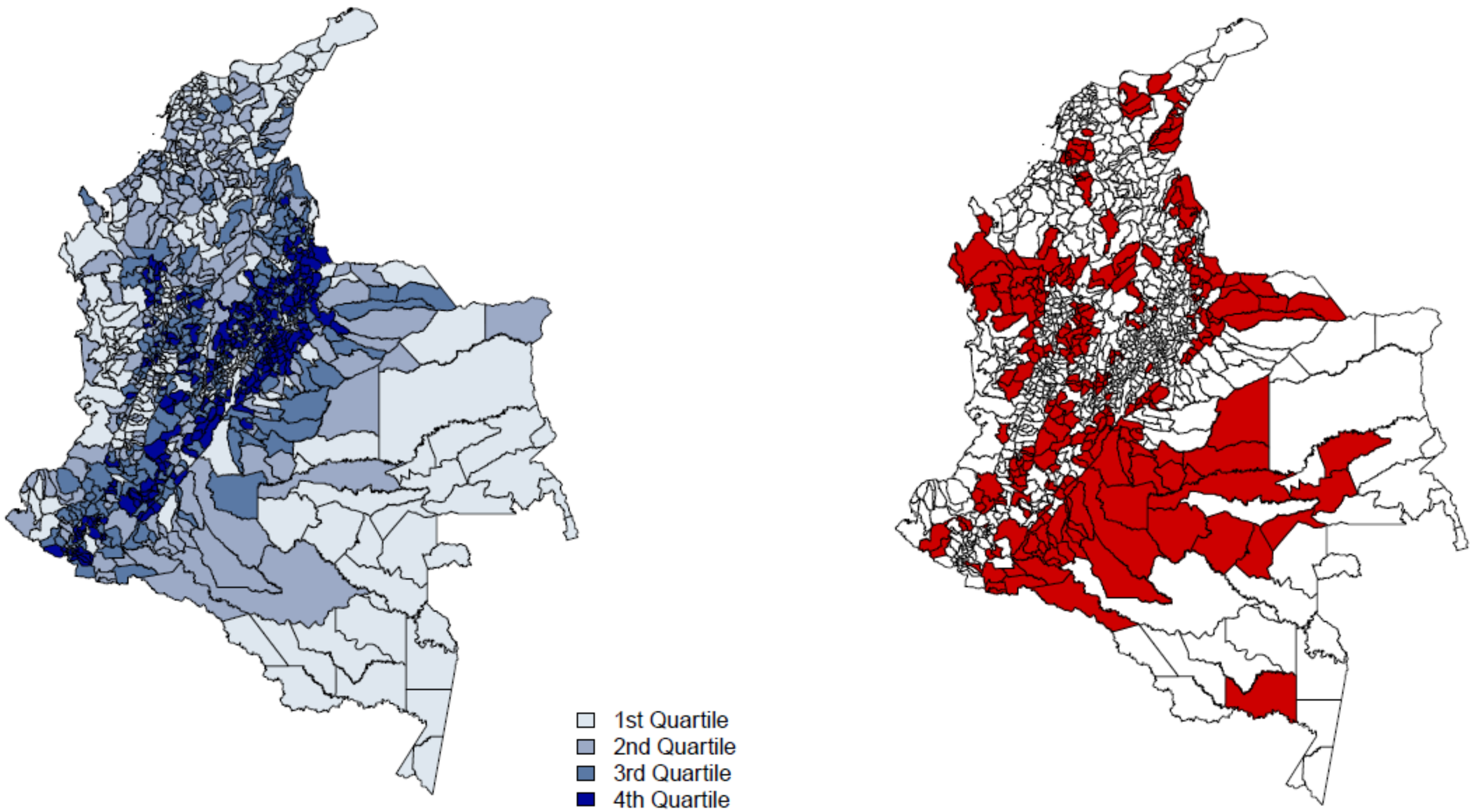
A Additional Figures and Tables

Figure A1: Monthly FARC Events Nationwide (1996-2014)



Notes: Figure shows the monthly number of conflict events involving FARC between January 1996 and December 2014. The solid line shows a centered six-month moving average. Dashed red lines denote the start of the sample period for our analysis of credit outcomes in January 2009 and the start of the negotiations period in June 2011 (i.e., Victims Bill).

Figure A2: Aggregate Loan Applications and FARC Exposure

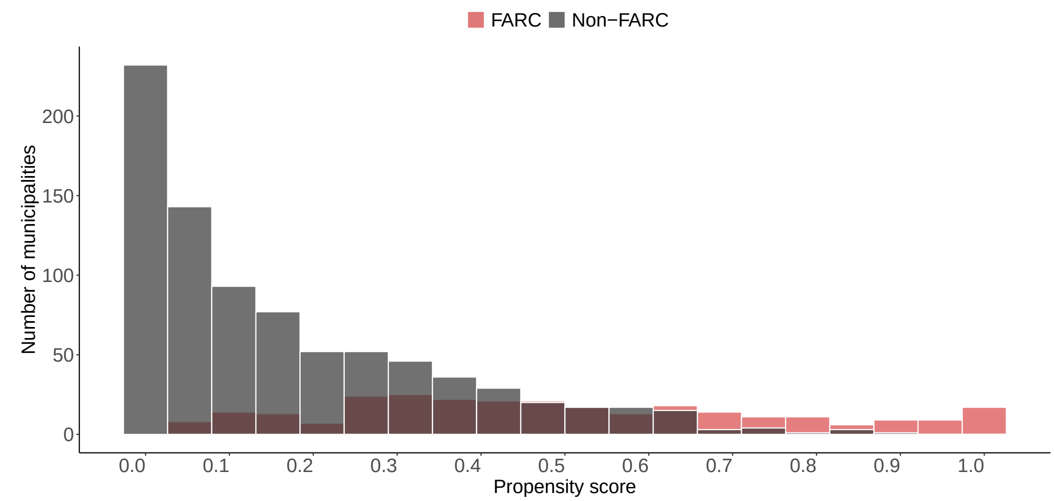


(a) Loan Applications per 10,000 inh. (2009-2019)

(b) FARC Exposure (1996-2008)

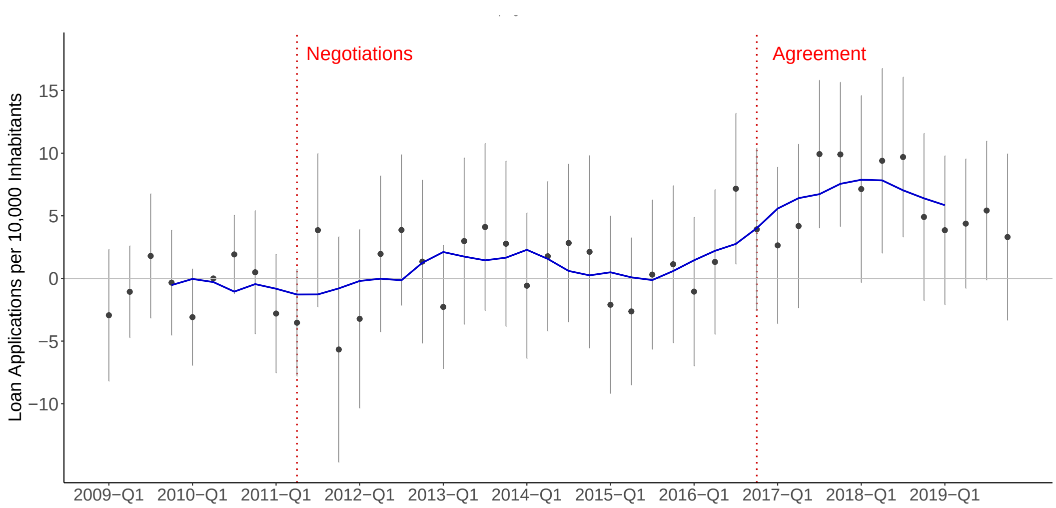
Notes: Panel (a) shows quartiles of the distribution of total loan applications to BAC per 10,000 inhabitants in the period 2009-2019. Panel (b) shows the municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008.

Figure A3: Distribution of Propensity Scores for FARC Exposure



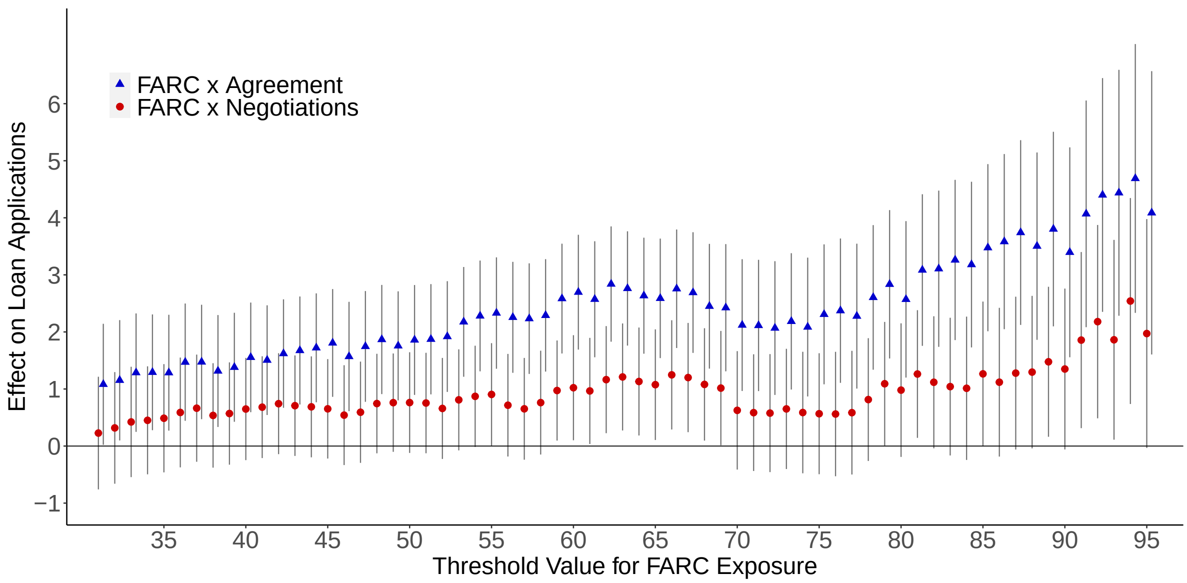
Notes: Figure shows the distribution of propensity scores for FARC exposure, disaggregated by actual exposure. FARC exposure takes a value of one for municipalities in the upper quartile of the distribution of total FARC events (per 10,000 inhabitants) between 1996 and 2008. The propensity scores are fitted values from a Probit regression of FARC exposure on 23 pre-determined municipal characteristics and department fixed effects, shown in Table A2. The common support ranges from 0.05 to 0.75 and includes 757 municipalities.

Figure A4: Loan Applications: Event Study (Municipality-Quarter Level)



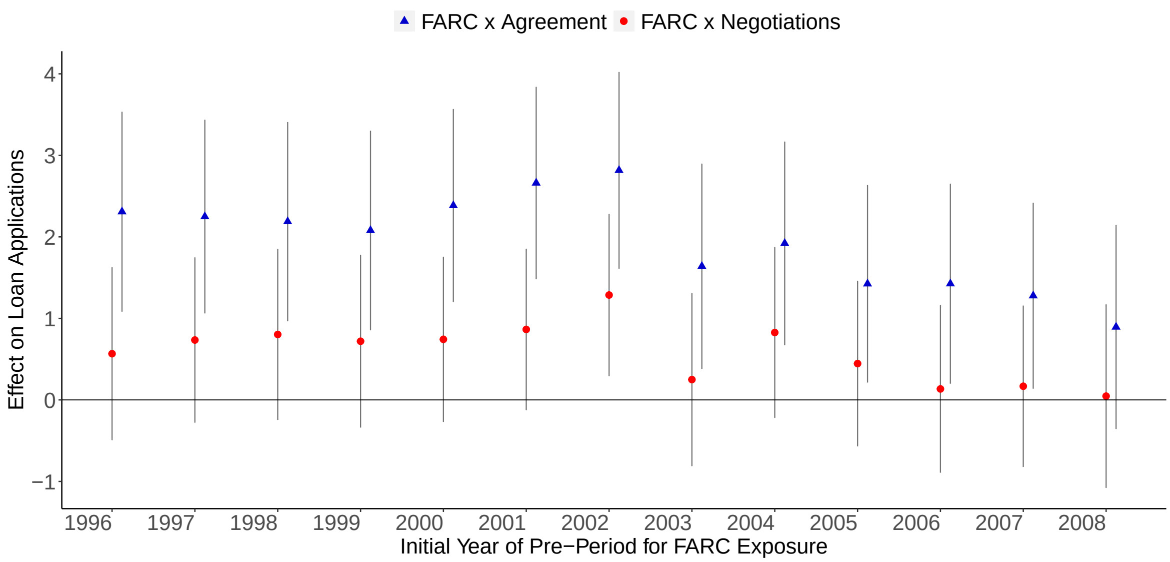
Notes: Figure shows point estimates and 95% confidence intervals from a regression of the number of loan applications (per 10,000 inhabitants) on quarter dummies interacted with an indicator for FARC municipalities (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008). Unit of observation: Municipality-quarter. Regression includes municipality and department-quarter fixed effects, as well as quarter dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The solid line depicts a centered six-quarter moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Figure A5: Loan Applications: Different Threshold for FARC Exposure



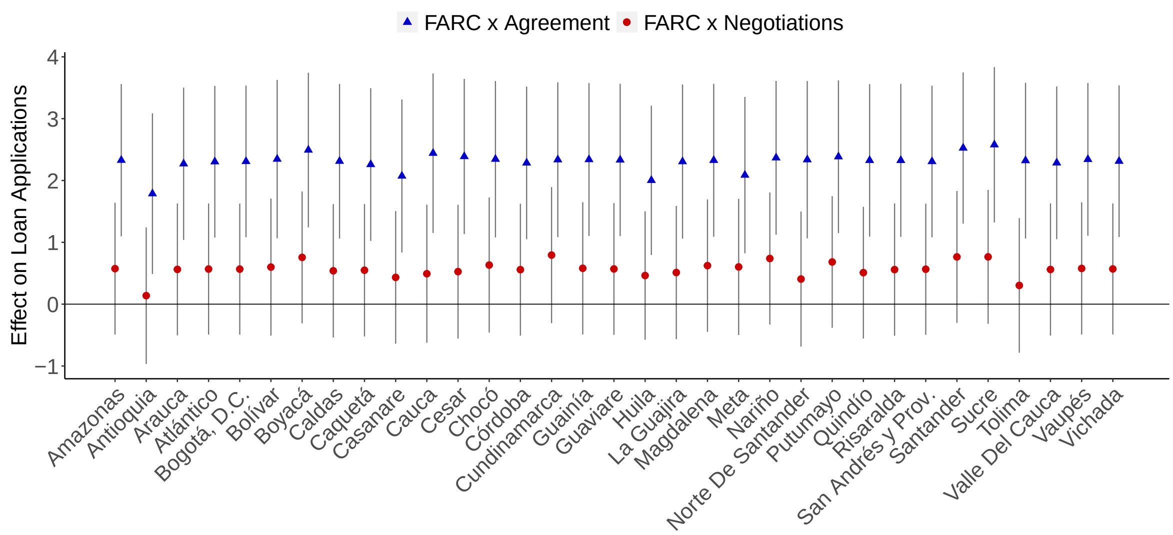
Notes: Figure shows point estimates and 95% confidence intervals from separate regressions of the monthly number of loan applications (per 10,000 inhabitants) on the interaction of a dummy for FARC exposure with separate dummies for the negotiations and agreement periods (i.e., our main specification). 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 = 75th percentile). 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors are clustered two-way by municipality and department-year.

Figure A6: Loan Applications: Different Periods of FARC Exposure



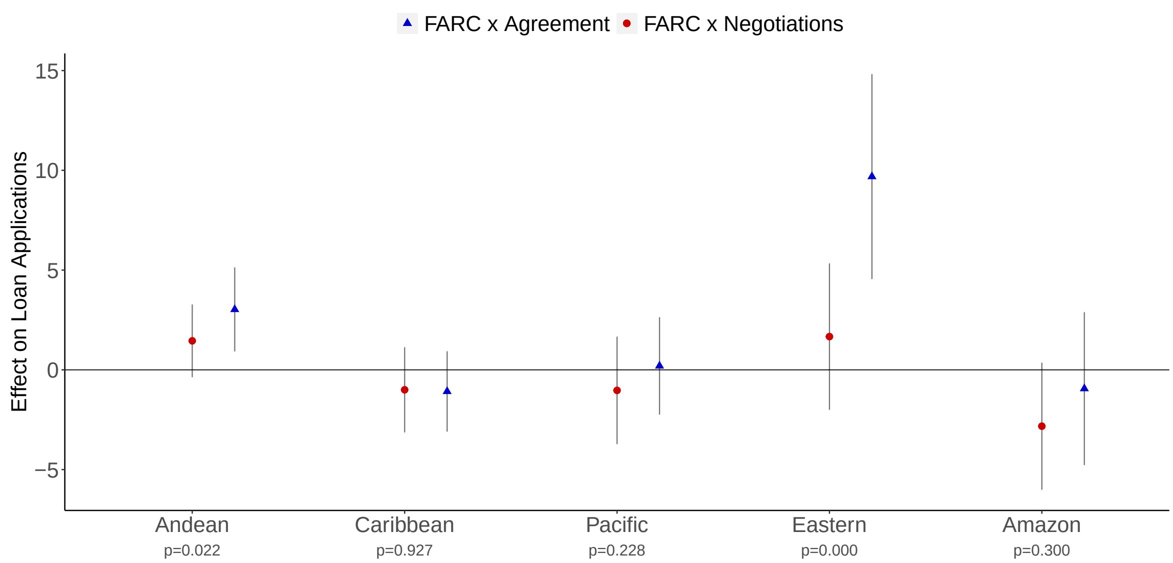
Notes: Figure shows point estimates and 95% confidence intervals from separate regressions of the monthly number of loan applications (per 10,000 inhabitants) on the interaction of a dummy for FARC exposure with separate dummies for the negotiations and agreement periods (i.e., our main specification). 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors are clustered two-way by municipality and department-year.

Figure A7: Loan Applications: Removing One Department



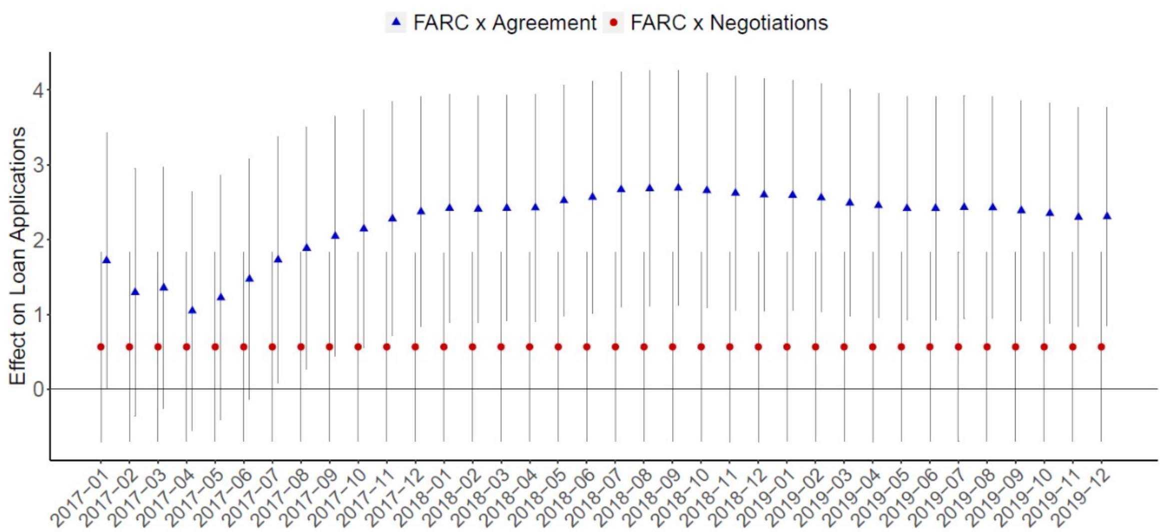
Notes: Figure shows point estimates and 95% confidence intervals from separate regressions excluding the department in the x-axis from the sample. The dependent variable is the monthly number of loan applications (per 10,000 inhabitants). The regressors of interest are the interaction of a dummy for FARC exposure with separate 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors are clustered two-way by municipality and department-year.

Figure A8: Heterogeneous Effects: Geographical Regions



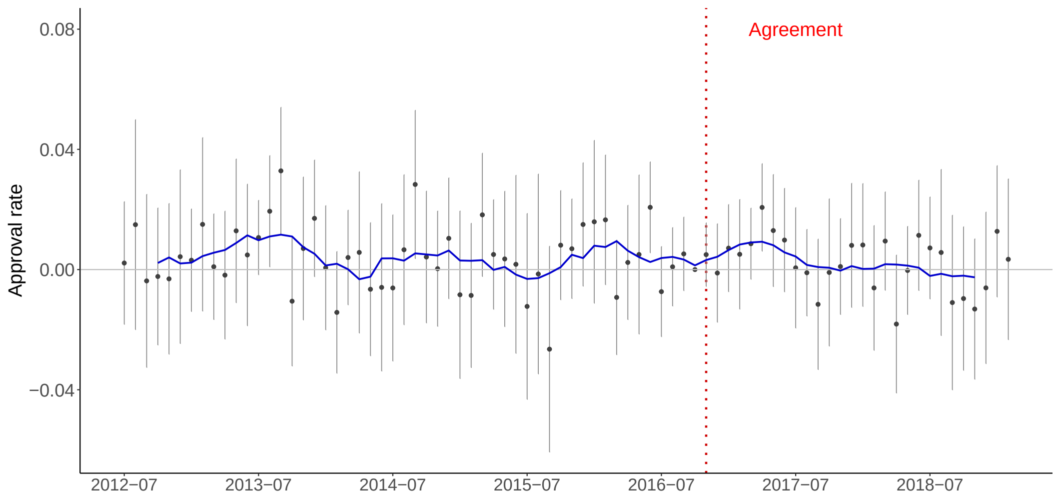
Notes: This figure shows point estimates and 95% confidence intervals from a regression with the loan application rate per 10,000 inhabitants as dependent variable. Municipalities are classified according to their geographical region. The regressors of interest are the interaction of a dummy for FARC exposure (i.e., upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996-2008) with separate dummies for the negotiations and agreement periods and separate dummies for each geographical 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The p-value shown in the x-axis corresponds to the null hypothesis of equal effects during the negotiation and agreement periods for each region. Standard errors are clustered two-way by municipality and department-year.

Figure A9: Loan Applications: Different Sample End Date



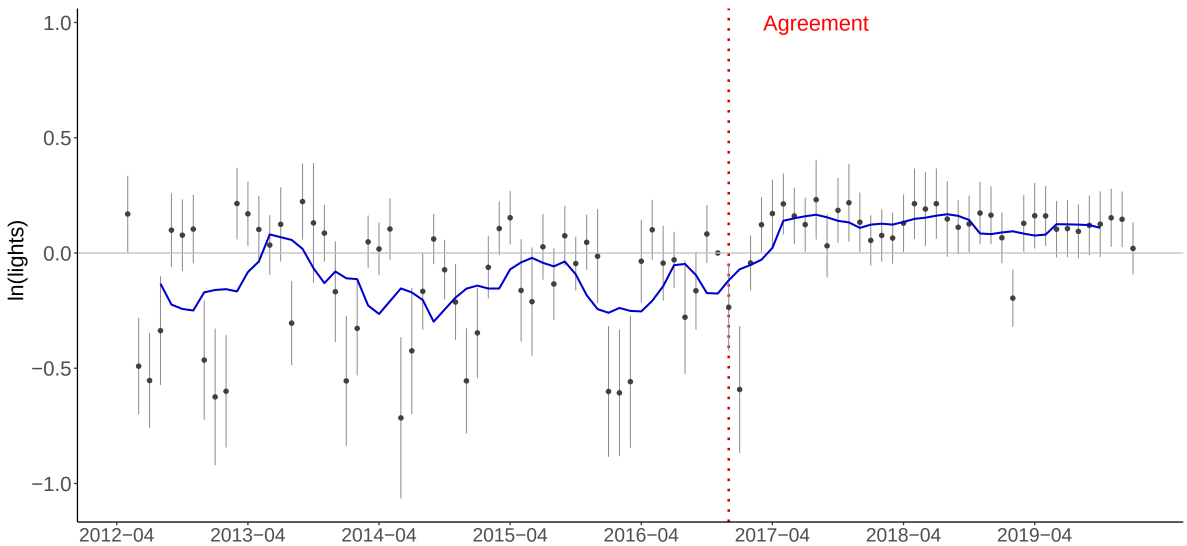
Notes: This figure shows point estimates and 95% confidence intervals from separate regressions in which the final month in the sample is indicated in the x-axis. The dependent variable is the monthly number of loan applications (per 10,000 inhabitants). The regressors of interest are the interaction 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation.. Standard errors are clustered two-way by municipality and department-year.

Figure A10: Loan Approval Rate: Event Study (Application Level)



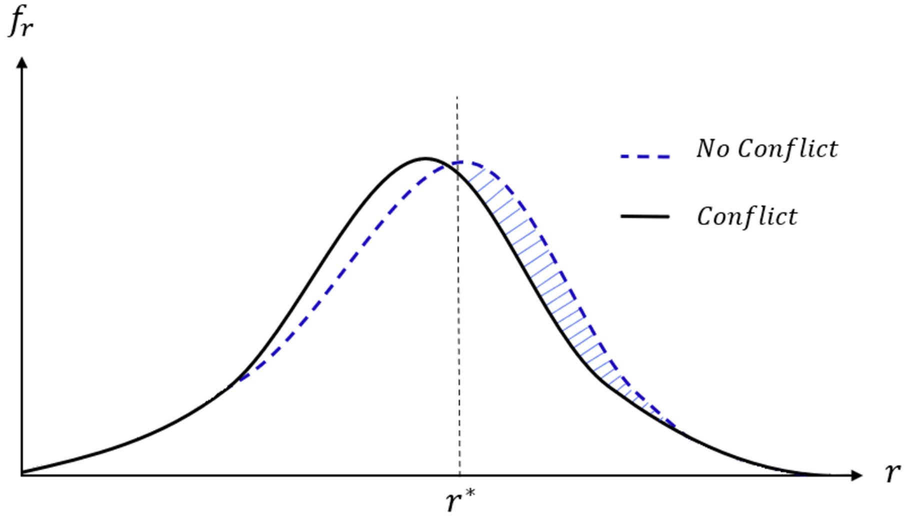
Notes: This figure shows point estimates and 95% confidence intervals from a regression of a dummy for loan approval on month dummies interacted with an indicator for municipalities with FARC exposure (i.e., in the upper quartile of the distribution of total FARC events per 10,000 inhabitants between 1996 and 2008). The unit of observation is the loan application. The regression includes municipality and department-month fixed effects, as well as additional sets of quarter fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Additional application level controls include the applicant's gender, intended use of loan, credit line, and regional headquarter where the loan originates, as well as the score awarded by the credit bureau at the initial stage and the credit score from BAC's own scoring models. The solid line depicts a centered six-month moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Figure A11: Night-Time Luminosity: Event Study (Municipality-Month Level)

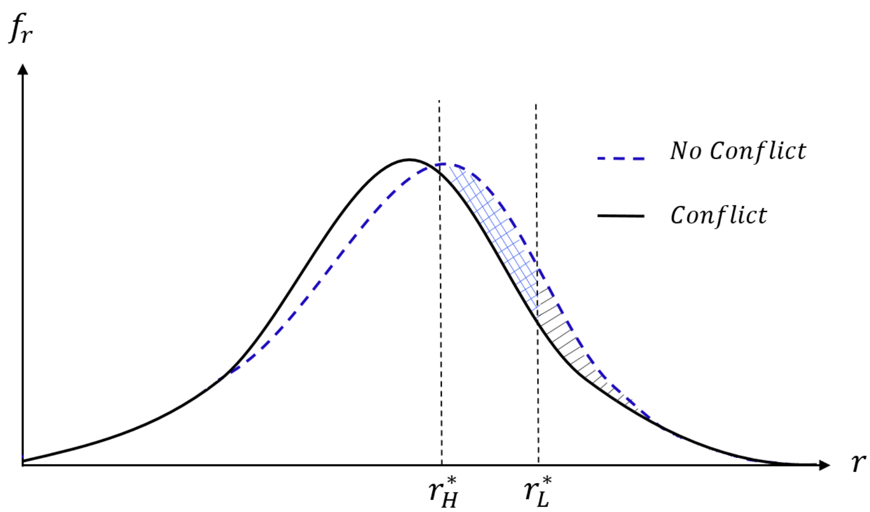


Notes: This figure shows point estimates and 95% confidence intervals from a regression of the log of night-time luminosity at the municipality-month level. Markers correspond to point estimates for monthly dummies interacted with an indicator for municipalities with FARC exposure (i.e., in the upper 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 night-time lights data is VIIRS. The regression includes municipality and department-month fixed effects, as well as additional sets of month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. The solid line depicts a centered six-month moving average of the point estimates. Standard errors are clustered two-way by municipality and department-year.

Figure A12: Visualization of Model with Heterogeneous Project Returns



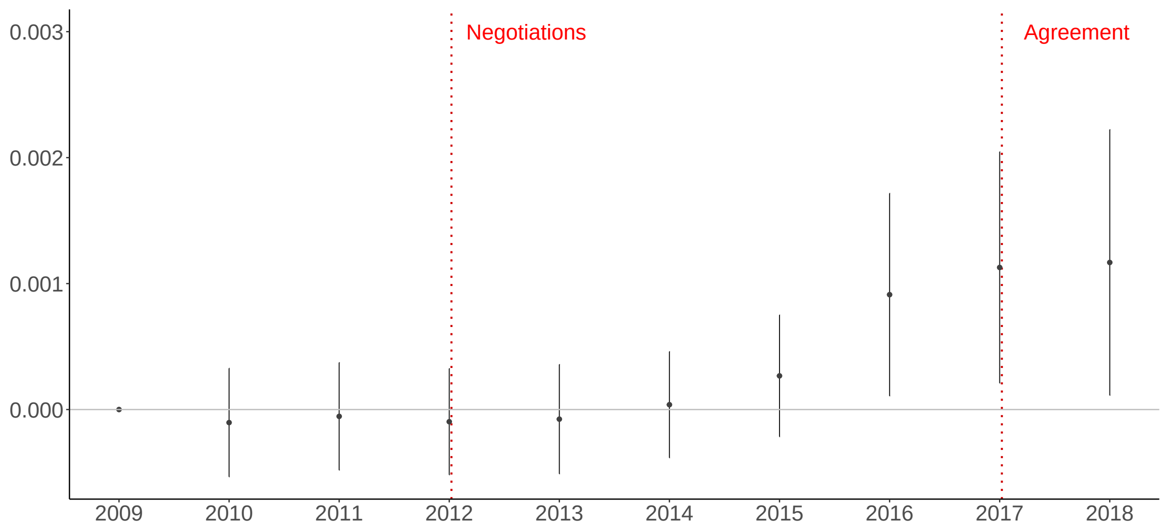
(a) Baseline Case



(b) Heterogeneous Thresholds by Market Access

Notes: Figures provide a visualization of the effect of conflict on investment in the model with heterogeneous project returns (i.e., r is a random variable). Panel (a) depicts the situation in which the peace deal shifts the distribution of returns to the right, thereby making some investment projects attractive enough to pursue (i.e., exceed the threshold return for indifference given by $r^\star$). The shaded area indicates the increase in investment (and in demand for credit) resulting from the end of conflict. In panel (b), heterogeneity across municipalities in access to markets affects the actual return given by $R = rm$, where m is a positive constant taking two possible values $m_{high} > m_{low} > 0$. Municipalities with high access to markets have a threshold $r^\star_H = r^\star/m_{high}$, while those with low access to markets have a threshold $r^\star_L = r^\star/m_{low}$, where $r^\star_L > r^\star_H$. 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 A13: Coca Cultivation: Event study



Notes: This figure shows point estimates and 95% confidence intervals from a regression of the share of municipal area devoted to the cultivation of coca on year 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. Regression includes municipality and department-year fixed effects, as well as year dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors 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	0.769	0.900	0.286	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 governmentguarantee	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	0.388	0.366	0.235	82562
Average assets	58.857	58.386	14.433	82562
Average yearly income	3.988	3.325	2.189	82562

Notes: The unit of observation is the municipality-month. **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 include cultivation of crops, livestock, fishing, and forestry. 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. **Panel B:** Average amount disbursed and total amount disbursed are measured in millions of 2019 COP. The average interest rate is defined as percentage points above reference rate DTF (average return on fixed term deposits in Colombia). Government guarantees include FAG and FNG. **Panel C:** Outcomes include the share of disbursed loans that go 60 or 120 days past due within the first year 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. **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 is defined as the percentage of clients whose highest degree of education is secondary or higher. Applicant's average assets and yearly income are measured in millions of 2019 COP.

Table A2: Municipal Characteristics and FARC Exposure

	Mean		P-value (1) = (2)	LASSO	Probit	N
	∼ FARC	FARC				
	(1)	(2)	(3)	(4)	(5)	(6)
Population (x 1,000)	47.439	16.208	0.001	0	-0.010***	1122
Altitude (meters)	1148.369	1116.872	0.761	0	0.0002**	1122
Area (hectares x 1,000)	88.052	142.785	0.007	0	-0.0001	1122
𝟙(Departmental capital)	0.037	0.007	0.000	0	-0.612	1122
Rural share of population	0.560	0.638	0.000	1	0.5	1122
𝟙(BAC branch)	0.600	0.730	0.000	1	0.372**	1122
Distance to nearest BAC branch (Km)	9.227	8.046	0.458	0	0.001	1122
Distance to departmental capital (Km)	80.712	83.690	0.431	0	-0.001	1122
Distance to nearest market (Km)	131.839	124.394	0.262	0	-0.005***	1122
Distance to Bogotá (Km)	324.964	311.342	0.250	0	0.003***	1122
Literacy rate	84.570	81.726	0.000	0	-0.017*	1122
Infant mortality rate	22.999	25.948	0.000	0	0.006	1122
Coffee cultivation (share of area)	0.007	0.006	0.051	0	-5.98	1122
Corn cultivation (share of area)	0.004	0.002	0.000	1	-16.387	1122
Rice cultivation (share of area)	0.002	0.001	0.009	0	-27.090**	1122
Sugar cane cultivation (share of area)	0.005	0.002	0.001	1	-5.661	1122
Banana cultivation (share of area)	0.003	0.002	0.000	1	-56.000***	1122
Oil palm cultivation (share of area)	0.001	0.000	0.011	0	-37.175*	1122
Yucca cultivation (share of area)	0.001	0.001	0.011	0	-21.261	1122
Potato cultivation (share of area)	0.003	0.000	0.000	1	-106.154***	1122
Cacao cultivation (share of area)	0.000	0.001	0.379	0	9.781	1122
Beans cultivation (share of area)	0.001	0.001	0.160	0	-0.795	1122
Coca cultivation (share of area)	0.000	0.001	0.000	1	150.828***	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
Imputed 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 year-olds 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 rate is taken from the 2005 census. Infant 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 total FARC attacks per 10,000 inhabitants between 1996-2008. The p-value in column 3 corresponds to the null hypothesis of equal means in FARC and non-FARC municipalities. Column 4 shows the optimal controls selected by LASSO, while column 5 shows coefficients from the Probit regression used to calculate the propensity scores of each municipality. 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: Municipal Characteristics and FARC Exposure (PSW)

	Mean		P-value (1) = (2)	N
	∼ FARC	FARC		
	(1)	(2)	(3)	(4)
Population (x 1,000)	16.51	14.585	0.074	757
Altitude (meters)	1064.244	1120.491	0.343	757
Area (squared kilometers)	86.551	99.078	0.336	757
𝟙(Departmental capital)	0.008	0.009	0.823	757
Rural share of population	0.626	0.644	0.222	757
𝟙(BAC branch)	0.767	0.714	0.097	757
Distance to nearest BAC branch (Km)	7.2	8.476	0.46	757
Distance to departmental capital (Km)	79.537	81.575	0.6	757
Distance to nearest market (Km)	110.028	115.273	0.415	757
Distance to Bogotá (Km)	316.589	308.777	0.525	757
Literacy rate	81.885	81.766	0.857	757
Infant mortality rate	25.15	25.477	0.659	757
Coffee cultivation (share of area)	0.007	0.007	0.828	757
Corn cultivation (share of area)	0.002	0.002	0.848	757
Rice cultivation (share of area)	0.001	0.001	0.823	757
Sugar cane cultivation (share of area)	0.002	0.003	0.368	757
Banana cultivation (share of area)	0.001	0.002	0.564	757
Oil palm cultivation (share of area)	0.000	0.000	0.19	757
Yucca cultivation (share of area)	0.001	0.001	0.984	757
Potato cultivation (share of area)	0.000	0.000	0.591	757
Cacao cultivation (share of area)	0.000	0.000	0.943	757
Beans cultivation (share of area)	0.001	0.001	0.387	757
Coca cultivation (share of area)	0.000	0.000	0.948	757

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 rate is taken from the 2005 census. Infant 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. In columns 1-2, FARC municipalities are those in the upper quartile of the distribution of total FARC attacks per 10,000 inhabitants between 1996-2008. The sample is restricted to the common support of the propensity score for FARC exposure, based on the Probit regression in column 5 of Table A2. Control observations are also weighted by the inverse of a non-parametric function of the propensity score. The p-value in column 3 corresponds to the null hypothesis of equal means in FARC and non-FARC municipalities. Column 4 shows the number of municipalities with available data for each variable. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Conflict Intensity (2009-2019)

	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)
$FARC_i \times Negotiations_t$ [a]	-0.082**	-0.009	0.472	10.606***	0.002	-0.213	-27.054**	-2.661***	-0.667***	-0.980	-0.088**	-0.008	-0.025
(2012-2016)	(0.034)	(0.084)	(1.059)	(3.205)	(0.064)	(0.135)	(10.857)	(0.536)	(0.147)	(1.533)	(0.041)	(0.029)	(0.038)
$FARC_i \times Agreement_t$ [b]	-0.229***	-0.071	-0.573*	0.601	-0.092	-0.374***	-59.210**	-3.565***	-0.885***	-1.943	-0.190***	-0.062	-0.163***
(2017-2019)	(0.045)	(0.097)	(0.311)	(2.098)	(0.101)	(0.105)	(23.463)	(0.675)	(0.171)	(2.063)	(0.046)	(0.047)	(0.040)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12342	12342	12342	12342	12342	12342	12342	12342	12342	12342	12342	12342	12342
R-Squared	0.615	0.149	0.291	0.586	0.448	0.242	0.491	0.509	0.361	0.357	0.342	0.392	0.415
Mean DV	0	0.073	1.999	10.506	0.287	0.294	78.889	2.409	0.203	2.055	0.146	0.043	0.099
p-value H_0: [a] = [b]	0	0.097	0.353	0.015	0.306	0.052	0.078	0.001	0	0.396	0.015	0.022	0.003

Notes: The unit of observation is the municipality-year. The dependent variables are taken from the Colombian Registry of Victims managed by UARIV. 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 between 2017 and 2019 (both inclusive). Sample period: 2009-2019. All regressions include municipality and department-year fixed effects. Additional controls include year dummies interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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)
$\text{FARC}_i \times \text{Negotiations}_t$ [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)
$\text{FARC}_i \times \text{Agreement}_t$ [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 × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Population quartile × Month FE	No	No	Yes	No	No	No
Municipal category × 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 number of loan applications 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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: Loan Applications: Additional Variables in LASSO and PSW

	Dependent variable: Loan Application rate			
	LASSO		Propensity Score	
	Few missings	All	Few missings	All
	(1)	(2)	(3)	(4)
$\text{FARC}_i \times \text{Negotiations}_t$ [a]	0.190	0.227	0.555	0.800
	(0.660)	(0.666)	(0.914)	(1.064)
$\text{FARC}_i \times \text{Agreement}_t$ [b]	1.922**	2.163***	2.067**	2.159*
	(0.773)	(0.798)	(0.980)	(1.160)
Municipality FE	Yes	Yes	Yes	Yes
Department × 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, we include 37 municipal characteristics with few missing values 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 A7: Cross-sectional Correlation of Municipal Characteristics Used for Heterogeneous Effects

	Access to		Share	Land
	Dpt. capital	Bogotá	Non-Poor	Restitution
Access to Market	0.314***	0.595***	0.367***	-0.104*
Access to Dpt. capital	-	0.065	0.324***	-0.108*
Access to Bogotá	-	-	0.322***	-0.003
Share Non-Poor	-	-	-	-0.135**

Notes: This table shows correlations between time-invariant municipal characteristics. Access to wholesale market, to the departmental capital and to Bogotá is measured based on the distance in kilometers. The share above the poverty rate is based on the index of Unmet Basic Needs (UBN) in the 2005 census. Land restitution corresponds to the total number of claims for land restitution between 2011 and 2020 (per 10,000 inh. in 2008), based on the administrative records held by the government agency for land restitution (URT). *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Other Heterogeneous Effects

	Heterogeneity based on:						
	Extensive margin		Above/below Median				
	PDET	FARC camps	Soil quality		Other Armed Groups		Coca Growth
			Accretion	Suitability	1987-2008	2009-2014	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{FARC}_i \times \text{Negotiations}_t$ (Low) [a]	0.763	0.620	0.339	0.561	0.387	0.593	0.795
	(0.774)	(0.651)	(0.694)	(0.886)	(0.888)	(0.729)	(1.109)
$\text{FARC}_i \times \text{Negotiations}_t$ (High) [b]	0.132	-0.413	0.773	0.552	0.729	0.489	0.566
	(0.909)	(1.765)	(0.958)	(0.775)	(0.811)	(0.849)	(0.702)
$\text{FARC}_i \times \text{Agreement}_t$ (Low) [c]	2.637***	2.400***	2.420***	2.910***	2.568**	2.277***	2.784***
	(0.936)	(0.763)	(0.855)	(1.011)	(1.088)	(0.862)	(0.999)
$\text{FARC}_i \times \text{Agreement}_t$ (High) [d]	1.581*	0.615	2.335**	1.749*	2.073**	2.399***	2.272***
	(0.875)	(1.237)	(1.102)	(0.911)	(0.903)	(0.912)	(0.824)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,104	148,104	146,784	146,784	148,104	148,104	148,104
R-Squared	0.707	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	17.963
p-value H_0: [c] = [d]	0.366	0.156	0.947	0.339	0.708	0.909	0.636
p-value H_0: [b] = [d]	0.013	0.438	0.031	0.078	0.034	0.004	0.002

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 3-7, 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. In column 7, we use the growth rate in the share of municipal area devoted to the cultivation of coca between 2014 and 2018. 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 predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Other Loan Outcomes

	Apps. w/ Credit Score	Share of Disbursed Loans							
		Audit	30 Days Past Due		120 Days Past Due		Outstanding		Extended Payments
			Year 1	Years 1-2	Year 1	Years 1-2	30 Days	120 Days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\text{FARC}_i \times \text{Negotiations}_t$ [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)
$\text{FARC}_i \times \text{Agreement}_t$ [b]	-0.002	0.019*	0.003	0.003	0.0002	-0.004	-0.002	-0.003	0.008
	(0.005)	(0.011)	(0.003)	(0.006)	(0.002)	(0.004)	(0.007)	(0.006)	(0.009)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Start (MM/YY)	07/12	07/11	01/09	01/09	01/09	01/09	01/09	01/09	01/09
Sample end (MM/YY)	12/19	12/19	12/17	12/17	12/17	12/17	12/19	12/19	12/10
Maturity of Loans	-	Any	Any	Any	Any	Any	Any	Any	≤ 2 Years
Observations	82,562	88,931	108,470	108,470	108,470	108,470	143,881	143,881	83,021
R-Squared	0.390	0.488	0.249	0.295	0.182	0.271	0.777	0.771	0.248
Mean DV	0.87	0.223	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 header. Observations lacking applications in column 1 or disbursed loans in columns 2-9 are excluded from the sample. The outcome in column 1 is the share of applications with a credit score from a Credit Bureau. In column 2, it is the share of disbursed loans with an in-person visit to the investment site. Columns 3-6 calculate the share of disbursed loans that entered into periods of 30 or 120 days past due within the first year or first two years after disbursement. Columns 7-8 calculate the share of outstanding loans per municipality-month that are 30 or 120 days past due. The outcome in column 9 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 in all columns include month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. 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: Night-Time Luminosity

	ln(lights)	
	(1)	(2)
$FARC_i \times Agreement_t$	0.231***	0.140***
	(0.039)	(0.025)
Municipality FE	Yes	Yes
Department × 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 night-time lights, based on VIIRS luminosity data. $FARC_i$ 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 in all columns include month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Loan Applications: Agricultural Destinations

	Cattle	Coffee	Fruits	Plantain	Cocoa	Sugarcane	Pigs	Potato	Aquaculture	Small Species
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\text{FARC}_i \times \text{Negotiations}_t$ [a]	0.006	-0.010	0.007	-0.002	0.007*	-0.002	-0.0004	-0.001	0.001	0.002
	(0.009)	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
$\text{FARC}_i \times \text{Agreement}_t$ [b]	0.003	-0.015*	0.011**	-0.002	0.012***	-0.002	0.010***	-0.002	0.001	0.003
	(0.011)	(0.009)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Department × 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	136,055	136,055	136,055	136,055	136,055	136,055	136,055	136,055	136,055
R-Squared	0.629	0.754	0.587	0.577	0.562	0.672	0.369	0.664	0.706	0.358
Mean DV	0.256	0.138	0.063	0.041	0.028	0.025	0.027	0.015	0.014	0.009
p-value H_0: [a] = [b]	0.618	0.472	0.280	0.996	0.159	0.881	0.001	0.054	0.875	0.531

Notes: The unit of observation is the municipality-month. The dependent variable is the share of loan applications with the intended destination listed in the header. 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 are month fixed effects interacted with predetermined measures of (i) rural share of population, (ii) cultivated agricultural crops, (iii) coca cultivation. Standard errors clustered two-way by municipality and department-year are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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.

Construction of the Samples

This section 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 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 lack information on the destination 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 application-level information of all the applications that go through the scoring models between July 2012 and February 2019. This contains a total of 2,105,369 observations. 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 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 for at least 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 of 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 number 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 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.

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 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 or higher as percentage of total loan applications in scoring models 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.

- Share of applications with credit score: Share of loan applications per municipality-month with a non-missing credit score from a credit bureau. 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 the client takes 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. FARC municipalities are classified 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. FARC municipalities are classified 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 terrorist 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 the 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 standardized 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.