Peer Effects and Recidivism: Wartime Connections and Criminality among Colombian Ex-combatants

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Abstract

To what extent do peers affect criminal behavior? In this paper, I study peer effects among ex-combatants in Colombia. Following a theoretical framework that differentiates the impact of economic conditions from that of social networks, I rely on individual-level data on over 16,000 former paramilitaries in Colombia to study the relationship between illegal gold production and recidivism. I show that when the economic benefits of illegal sectors increase, ex-combatants favor criminal activities. More importantly, I show that an increase in wartime peers' criminality increases an ex-combatant's criminal activity. I complement these results with the analysis of an original survey about the social connections of ex-combatants and explore the potential effect of tackling wartime networks as a policy to reduce crime after conflicts.

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Introduction

During transitions from war to peace, countries struggle to control rising levels of crime, with evidence coming from diverse settings, ranging from a crime wave following the Napoleonic Wars around 1815 to present-day gang violence after the end of El Salvador's civil war in 1992. The continuation of violence after the transition to peace is often related to the failure to reintegrate ex-combatants and can pose a challenge to political and economic development. Given the evidence of increases in criminality after conflicts and the threat of remobilization, the policy research accompanying peace transitions has increasingly focused on the reasons why former combatants may engage in criminal activities. In this paper, I present evidence concerning the way local economic changes and wartime connections impact postconflict criminality among ex-combatants, expanding on the potential effects of peacetime policies in preventing crime and promoting reintegration.

While there is plenty of research on the continued violence after conflict, we still lack a clear understanding of the reasons why ex-combatants engage in criminal actions. Recent work has shown that, besides the classical motivations for engaging in delinquent activities, which include economic incentives and psychological factors (Collier, 1994; Weinstein, 2006), ex-combatants' contact with former fighters during the aftermath of conflict might be a crucial factor determining recidivism (Themnér, 2011; Daly, 2016). Such individuals are usually jobless, have mostly lost contact with their families and civilian acquaintances, and have only other fellow fighters with similar levels of criminal capital on whom to rely (Humphreys and Weinstein, 2007). According to this interpretation, it is possible that a peer effect drives ex-combatants to criminal activity. However, limitations in data availability have prevented researchers from making progress in the identification of these peer effects, and, more importantly, the estimation of their relevance, compared to other factors, in explaining postconflict criminality.

To overcome these limitations, in this paper I use individual-level panel data of postconflict criminal records of over 16,000 former paramilitary combatants in Colombia from 2013 to 2016. I match this information with detailed records about individual wartime experience and connections. The structure of the data enables me to differentiate the effect of economic changes that vary over time on delinquent behavior and separate the effect from the criminal activity of peers. I rely on a theory about peer effects in criminal behavior and derive explanations of criminality of former combatants. I argue that individual and social constraints shape the incentives and opportunities for ex-combatants to participate in illegal behavior: individual constraints refer to the opportunity cost provided by the surrounding context, such as proximity to an illegal market, and social constraints refer to the social network of the ex-combatant. Because the severity of these constraints may be affected by criminal activities, I study plausibly random variations to the economic local conditions, combined with the presence of partially overlapping groups of peers in the wartime network across municipalities, to estimate the effect of economic shocks separately from that of the peers' activity.

The observable implications of the argument are straightforward: I find that when the economic returns to the illegal sector increase, former combatants favor criminal activities. In particular, a one standard deviation increase in the economic shock is associated with an increase of around 0.375 ex-combatants' captures. More importantly, consistent with other theoretical accounts of crime, I show that an increase in the criminal activity of peers is likely to impact an ex-combatant's criminal behavior. A one standard deviation increase in wartime connections' captures is associated with an increase of around 0.484 ex-combatant's captures. The intuition is that changes in the economic returns to illegal activities taking place in certain municipalities will affect both (a) the opportunity cost of individuals living in those municipalities (individual economic effect) and (b) those individuals connected to them through social ties who live in unaffected municipalities (social level effect). Note that (b) is true *only* if a peer effect exists. The only way that a change that takes place elsewhere can affect an individual is through their connection to a peer who lives in a municipality that is experiencing changes in economic returns to criminal activities.

I complement the main results in several ways. First, I present consistent results across similar versions of the wartime network, severity of the economic changes, and crime measures. Second, I run several additional placebo tests with different commodities, outcomes, networks, and econometric specifications. I pay special attention to the mobility and connectivity of the units of analysis. Third, to explore the mechanisms, I show that the results are driven by collective crimes that require the participation of several acquaintances. Additionally, I conduct a dyad analysis rather than a group-level analysis to include additional individual-level controls. Finally, to validate the measures used in the main analysis, I analyze an original survey of ex-combatants that highlights the relevance of wartime connections for former paramilitaries in Colombia.

The results presented in this paper are directly relevant to policy debates concerning the most effective strategies for addressing the challenge of ex-combatant economic and social reintegration. To test the implications of the main finding, I analyze the potential effects of a policy that tackles the wartime connections related to crime and discuss the generalizability of the results.

This paper makes two main contributions. First, I use detailed individual panel data on criminal records and wartime connections to demonstrate the existence of peer effects among ex-combatants. Recent studies find evidence of the relevance of social factors in explaining recidivism (Daly, Paler and Samii, 2020; Kaplan and Nussio, 2018*b*); I deepen the analysis of these studies by exploiting exogenous economic variation and the presence of overlapping groups to carefully examine the relevance of peers and social networks. The paper also contributes to the literature on peer effects in comparative political science. The identification of peer effects within social networks is challenging; recently, political scientists have exploited exogenous variation and the use of more-detailed network data and strategies to examine the relevance of peers' behavior (Siegel, 2009; Christakis and Fowler, 2013), especially in American politics (Fowler et al., 2011; Sinclair, 2012). While many studies focus on the correlation between network characteristics and behavior, this paper aims to contribute to and expand the discussion about how to identify the impact of peer behavior (Alt et al., 2022; Kline and Tamer, 2020; Quispe-Torreblanca and Stewart, 2019; Larreguy and Teso, 2018; Acemoglu, Garcia-Jimeno and Robinson, 2015).

The rest of the paper proceeds as follows: in the following two sections I explain the theoretical motivation and context of the paper. In the next section I present the relevant aspects of a model of peer effects from which I derive the hypotheses and then introduce the data and identification strategy. In the final three sections I present the main results, discuss policy implications, and conclude with a discussion of limitations of the paper and avenues for future research.

Economic Changes and Peer Effects

Mounting evidence suggests that there is a high level of violence and crime in most postconflict contexts (Call, 2012; Kurtenbach and Rettberg, 2018). Although many scholars have studied the problem of postconflict crime, there is little consensus about the motivations of former fighters for reverting to violent and illegal behavior (Stedman, 1997; Walter, 1997; Berdal and Ucko, 2009; Muggah, 2008). For example, different reasons, including individual economic considerations and social circumstances, could potentially converge to affect the likelihood of recidivism.

Economic Returns and Postconflict Crime

How variations in economic conditions impact civil conflict (Dube and Vargas, 2013) and crime (Dix-Carneiro, Soares and Ulyssea, 2018) has been widely studied. The theoretical motivation for this effect can be traced back to classical economic studies of crime, according to which agents engage in criminal activities after performing a calculation of the cost and benefits that includes the opportunity costs of legal sector employment (Becker, 1968; Dal Bó and Dal Bó, 2011).[1] The effect of a commodity price shock will depend on many factors, including whether the commodity is legal or illegal, capital or labor intensive, or seasonal or not.[2] There is evidence that changes in the economic returns to the production and distribution of illegal commodities are associated with crime and violence (Sviatschi, 2022; Dell, 2015; Millán-Quijano, 2020; Mejia and Restrepo, 2013; Dube and Vargas, 2013). When illegal profits change, rates of criminality also change, for example because of variations in market shares or because the number of people involved in the illicit market varies.

Profits from illegal markets can fuel criminality in general and recidivism of ex-combatants in particular. To study variations in the ex-combatant's opportunity cost, I analyze municipal-level changes to illegal gold production. This commodity is at the core of the individual constraints that bind delinquent behavior, particularly in the developing context of Colombia, characterized by low state capacity and limited labor market opportunities. Especially relevant for our case study, the fact that the product is illegal gives former combatants a comparative advantage in this market. Ex-combatants possess knowledge of the functioning of illegal operations and the know-how required to make a profit from engaging in such activities (Valencia and Riano, 2017; Ortiz-Riomalo and Rettberg, 2018).

To simplify my argument, I hypothesize that ex-combatants' participation in criminal activities changes in response to changes in the economic returns to labor-intensive illegal commodities.

[1] For a review of crime and economic incentives, see Draca and Machin (2015) and Ferraz, Soares and Vargas (2021). A recent meta-analysis of the literature on economic shocks and violence by Blair, Christensen and Rudkin (2021) compares different possible mechanisms and the recent study by Rettberg et al. (2018) discusses the applications to Colombia.

[2] Economic variations could affect crime by changing local labor market conditions such as employment rates and earnings (Fougère, Kramarz and Pouget, 2009; Lin, 2008). Other potential mechanisms include the rapacity effect of a change to capital intensive goods (like appropriation of oil revenues) and an increase in public good provision (Di Tella and Schargrodsky, 2004).

Peer Effects and Postconflict Crime

Several scholars in sociology and criminology underscore the effect of social networks in crime decisions (Warr, 2002; Papachristos, 2014). According to this explanation, individuals participate in criminal activities as a result of the interaction with other delinquents. This approach suggests that delinquents have friends who have participated in crimes and that social ties are a means by which an actor is influenced to commit a crime (Sarnecki, 2001). In the same vein, following the seminal work of Glaeser, Sacerdote and Scheinkman (1996), recent theoretical approaches in economics relate crime to social networks. Several papers find that, in fact, crime and delinquency are related to positions in social networks.[3]

These studies suggest that properties of peer associations should be taken into account in order to better understand the relationship of social pressure and delinquent behavior in the aftermath of conflict and to inform delinquency-reducing policies targeted at ex-combatants. The reason to focus on wartime peers is threefold. First, recent studies show that different aspects of the social connections of an ex-combatant are important in explaining recidivism (Daly, Paler and Samii, 2020; Kaplan and Nussio, 2018*b*; Themnér, 2015, 2011). Second, wartime bonds lay the foundation for one of the most important social networks of ex-combatants following demobilization and during reintegration. Militancy often requires that combatants break links with family and friends, which in most cases implies a complete separation of military and civil life that is not always easy to bridge after conflict (Themnér and Karlén, 2020; Wood, 2008). The bonds created during a conflict are an important source of information (Parkinson, 2013; Staniland, 2014) and many ex-combatants actually retain their identity long after a conflict has ended (Daly, 2016). Third, the stigma against ex-combatants in postconflict societies (McMullin, 2013; Kaplan and Nussio, 2018*a*) may make them look to maintain contact and alliances with former peers. Consequently, although reintegration paths may differ, ex-combatants have in common at least one

[3] See, for example, Ballester, Calvó-Armengol and Zenou (2006); Patacchini and Zenou (2008); Mastrobuoni and Patacchini (2012); Liu et al. (2012).

set of 'weak ties': their former fellow combatants. These weak ties derive from bonds formed during wartime through socialization for long periods of time in small units while being exposed to constant threats.

Fellow ex-combatants remain an important source of information after a conflict has ended and units have demobilized. Even though these connections are not as 'strong' as family and friends, they are relevant in one key domain. Granovetter (1977, 2018) famously shows that weak ties are superior to strong ties in terms of providing support in getting a job.[4] Moreover, Patacchini and Zenou (2008) show that weak ties are positively related with crime decisions. Criminals transmit valuable information about criminal opportunities to potential accomplices. In other words, networks of criminals amplify delinquent behavior. As information about criminal opportunities is transmitted through social networks, an increase in the level of activity of peers in turn drives an increase in individual participation in criminal activities.

To simplify the second part of my argument, I hypothesize that ex-combatants will be affected by the level of criminal activity of their wartime peers. In particular, I argue that the overall criminal activity of the wartime connections will directly affect the decision of an ex-combatant to participate in criminal activities.

Context

Civil conflict has affected every region of Colombia. Left-wing guerrillas, right-wing militias, and groups involved in drug trafficking have proliferated since the 1980s and the consequences of their actions still resonate across the country (Romero, 2003). The paramilitary groups were created as a reaction by the landowning elite, drug barons, and the political class to the growth of rebel groups (Medina Gallego, 1990; López and Martínez, 2010) and were the main group responsible for war atroc-

[4] According to this argument, neighborhood-based close networks are limited when it comes to providing information about possible jobs. Recently, Alt et al. (2022) empirically develop this argument to show how unemployment shocks can transmit via social connections. I conduct an analysis similar to that of Alt et al. (2022), who look at the effect of an economic shock on individuals not directly affected by it, in table A.5 .

ities during a conflict that left over 220,000 dead and displaced more that 4.7 million, according to the Historical Memory Group (Comisión Nacional de Memoria Histórica) (CNMH, 2013).

After negotiations with the government of Álvaro Uribe, the self-defense paramilitary organization Autodefensas Unidas de Colombia (AUC) collectively demobilized between 2006 and 2007.[5] The militia organizations that composed the AUC showed considerable divergence in their postconflict trajectories (Daly, 2016). Almost half of the former factions remilitarized and some formed the backbone of criminal organizations that are still operating in the country (Watch, 2010; Daly, 2016; Fundacion Ideas para la Paz, 2017).

Although many factors could account for the overall dynamics of the reintegration and recidivism of an ex-combatant, this study seeks to identify the role of local economic conditions and peer effects. Because commodity price changes and wartime connections are important channels through which postconflict criminality responds to economic conditions and peer effects, I provide background information on these factors in the following subsections.

Illegal Commodities and Postconflict Crime in Colombia

Studies have shown the effect of commodity price changes on conflict and criminality in Colombia.[6] Following Rettberg, Cárdenas and Ortiz-Riomalo (2019), gold did not play a major role during the conflict, compared to coca, coffee, and oil, but has become one of the main focuses of criminal activity since the post-paramilitary demobilization. In the words of the Colombian National Police chief, 'Gold will have even more devastating effects than drug trafficking for the country' (cited in Rettberg,

[5] Two points are worth mentioning: one, individual demobilizations continued until 2012, as not all units demobilized in 2007; and two, the process was criticized for inflating the number of demobilized combatants. Multiple accounts of former paramilitary leaders and former government officials argue that the actual number of paramilitary combatants was lower than the initial number of over 30,000 members. In the data section I discuss the implications of these two considerations.

[6] See several examples in Blair, Christensen and Rudkin (2021).

Leiteritz and Nasi (2014)).[7] There are multiple opportunities for illegal groups to take advantage of mining activity: they can appropriate the value generated along the chain of gold production and even regulate the value chain in the territories where they are present.[8] For these activities, agents with experience in routes, the use of weapons, and engaging in violence are particularly valuable. In addition, agents with knowledge of trusted people to carry out these activities across different regions are of paramount importance.[9] Moreover, there are numerous documented cases of arrests related to illegal mining that spread though various municipalities where organizations consisting in part of former paramilitary members were known to operate. Section E of the appendix reports on instances of illegal gold-mining activities taking place in different municipalities and describes multiple cases in which ex-combatants were involved as a proof of concept of the mechanisms of the argument in this paper.

Illegal gold mining is a widespread activity in Colombia: based on the 2010 Mining Census, more than 62% of gold mines do not have a legal permit. The economic activity related to illegal gold mining is particularly vulnerable to predation; armed groups provide security along trafficking routes and in many cases exploit the mines. As such, illegal gold mining is an important source of revenue for organized criminal bands who control deposits and transit (Valencia and Riano, 2017). Significantly, disputes over control of the illegal activity spread beyond the locations of the mines. The actors involved are often located along trafficking routes and have developed the criminal capacity for extortion in several locations.

[7] The same comparison was made by the Colombian Attorney General, according to Rubiano (2017).

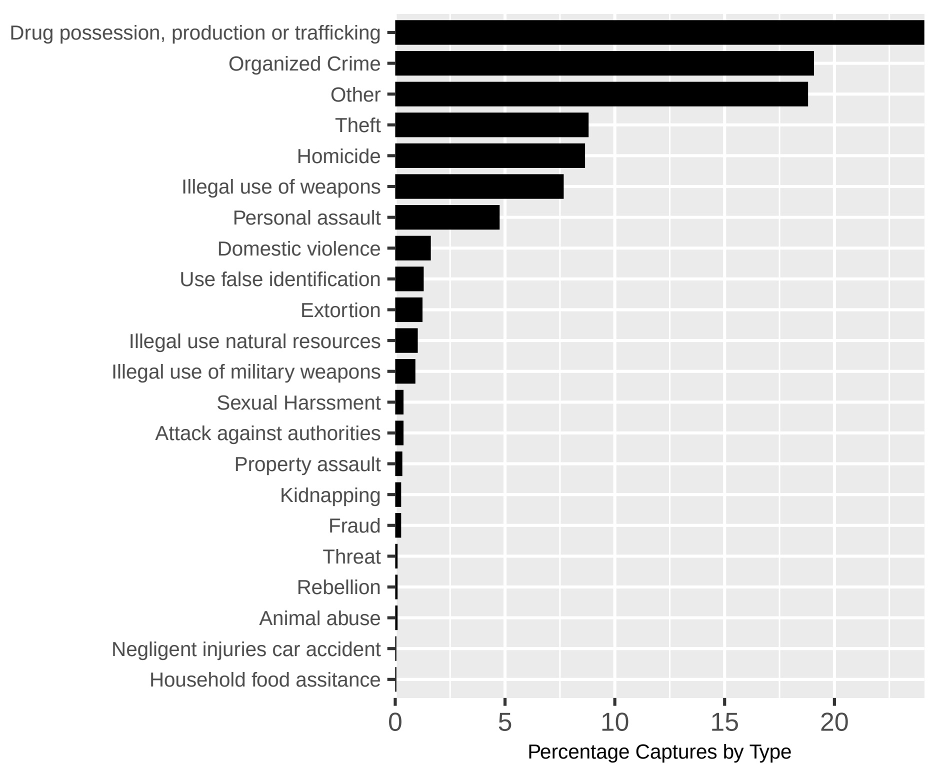
[8] Ortiz-Riomalo and Rettberg (2018) provide evidence that nonstate armed agents have mediated in the development of the illegal gold mining industry, 'especially in regions far from the main smelting and marketing centers. In this way, they gain access to the process of declaration, settlement and distribution of profits generated.'

[9] Using evidence from different contexts, von Lampe and Johansen (2004) present a typology of how various types of crime entail high levels of trust between partners.

Wartime Connections and Postconflict Crime among Colombian Ex-combatants

A considerable number of ex-combatants in Colombia resumed criminal activities undertaken during the conflict after demobilization, many as a result of their ongoing contact with former commanders (Daly, Paler and Samii, 2020) and many as a result of weak family ties and the presence of illegal markets (Kaplan and Nussio, 2018*b*).[10] Based on the number of arrests, around 15% of former paramilitary members participated in illegal activities in the years after demobilization, with their participation in crimes being spread across more than 900 municipalities across the country. Figure A.1 shows the location and spread of arrests of ex-combatants in the country. Former paramilitary members participate more frequently in collective crimes.[11]

Figure 1: Types of Crimes of Ex-combatants, 2013–2016



[10] These studies analyze data on both guerrilla (FARC, ELN, EPL) and paramilitary (AUC) organizations.
[11] Table A.7 in section E.2 presents a comparison of national levels of crime with ex-combatants' level and types of crime.

Three facts are worth mentioning about the collective nature of ex-combatant criminality. First, Figure 1 shows the frequency of arrest across types of crimes. The most common types of crimes are related to drug trafficking, organized crime, and possession of arms. Generally, these activities need the cooperation of several individuals to take place. Success in these activities depends on the collective participation of co-offenders (or knowing someone with connections and access to illegal markets). In fact, the National Police of Colombia uses the category of 'gang-related' crime to refer to these crimes and to distinguish them from other 'individual' crimes.

Second, we can approximate whether ex-combatants were arrested together. To that end, we can explore the density of arrests across different periods to see whether there is evidence of overdispersion (Glaeser, Sacerdote and Scheinkman, 1996) or even bimodality (Gaviria, 2000) in the crime distribution, meaning that several offenders must have acted together. If we see a multimodal geographical distribution, this reflects the fact that most places have few arrests (as expected) and a significant number of places have *many* arrests, which suggests that multiple participants were involved in criminal activities together. Figure A.2 shows the densities of arrest rates across Colombian municipalities for different years and, following (Gaviria, 2000), it provides suggestive evidence of collective participation in crime.

Finally, as preparation for this paper, I conducted a national survey of ex-combatants in Colombia to capture some patterns of their social connections. The idea was to capture the type of connections that are more relevant during conflict and how those relations vary after demobilization. I present the results broken down by each type of armed group, because the sample includes members who participated in a collective demobilization (Paramilitary) and those who demobilized individually (Guerrilla). The description of the survey strategy and results are provided in section K. Figure A.9 shows that combatants spent more time with members of their same unit and their same rank than with commanders or combatants of other ranks and units. After demobilization, the connection with ex-combatants is stronger with peers in the same unit and of the same rank than with other ex-combatants but lower than with family and close friends.

Therefore, the increasing presence of both criminal bands and illegal markets and the participation of ex-combatants in both, combined with the recent peace process that disarmed thousands of former fighters, make the study of the implications of wartime legacies on recidivism and criminality in Colombia particularly relevant.

Empirical Strategy

The identification of peer effects within social networks is challenging for several reasons. There are two main problems, as explained in figures 2 and 3. First, the investigation of the effect of a ex-combatant i's criminal behavior on the criminal behavior of an ex-combatant j to whom i is connected may be affected by a 'reflection problem' (Manski, 1993). This refers to the possibility that a correlation in the criminal behavior of two ex-combatants, i and j, is because either i's criminal effort is affecting j's criminal effort or vice versa. A second problem is that of 'common shocks.' Specifically, unobserved common shocks might affect the behavior of ex-combatants who are connected and might be the underlying reason for the observed correlation in their behavior. It is possible to incorrectly attribute a change in i's behavior to k's behavior, when in fact both are being affected by the same shock in location X.

Figure 2: Reflection Problem

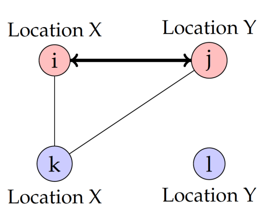


Figure 3: Common Shock

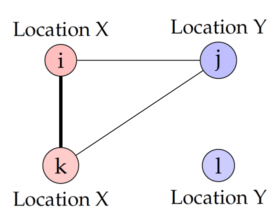
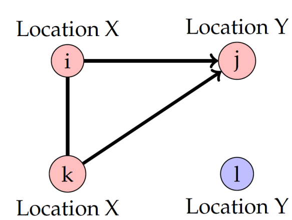


Figure 4: Peer Effect



For the identification of peer effects, ideally we would find a treatment that randomly affects a unit in the group (locally/specifically) and then estimate how the unit's behavior (outcome) would affect the outcomes of other units in the network. This means that for the economic change to be local, it would be ideal for the change in economic returns to be at the individual level. In our approach, the treatment could be similar for several group members in similar municipalities (units j and l in Y in figures 2 – 4). However, because they may belong to different networks, the treatment will enable us to see how their behavior, and not another factor, can affect the outcome of other network members.

I address the main empirical challenges related to identification of peer effects by taking advantage of the panel structure of the data and the presence of overlapping wartime groups across municipalities to calculate the effect of the economic shock on one municipality as it transmits to connected peers in other municipalities, including group (wartime), time (year), and location (municipality) fixed effects. The idea behind the strategy is that it estimates how the effect on some units of analysis, for example i and k, transmits to other units of analysis, j (but not to l), through their connection in the wartime network. Put differently, I estimate to what extent an economic shock that does not necessarily affect the municipality of an ex-combatant may still have an effect on his criminal record through his wartime connections.

To further explain the identification strategy, I rely on popular models that have been developed to describe the relationship between social networks and crime. In what follows, I present a simplified version of one such model, based on a synthesis by Calvó-Armengol, Patacchini and Zenou (2009), Ballester, Calvó-Armengol and Zenou (2006), and Calvó-Armengol and Zenou (2004).[12] The model departs from the idea that the decision to put effort into criminal activities is affected by local economic conditions (e.g., presence of legal and illegal markets) and by social networks (e.g., criminal activity of peers, social connections involved in crime). Therefore, the model not only reflects the main elements discussed in this paper, but also enables the empirical separation of the effect of economic conditions from peer effects.

[12] The general version of this kind of model, network games with quadratic payoffs, is explained in the textbook by Jackson (2010), pp. 290–292. For a review of applications of this model to crime, see Lindquist and Zenou (2019).

Networks and Crime

There are many variants to models of crime and social interactions, all of which are similar to the specification that is considered in this section. Individuals are connected to each other through a social network represented by an adjacency matrix g, where $g_{ij} = 1$ if i and j are linked to each other and $g_{ij} = 0$ otherwise.[13] In figure 4 agents i, j, and k belong to the same wartime network while l belongs to another network.

In each period t, individuals indexed by i who are members of group g choose a level of criminal effort $y_{it} \geq 0$ and obtain an utility $u_{it}(\mathbf{y})$ that depends on the group's criminal profile $\mathbf{y} = (y_1, y_2, ..., y_n)$ in the following way:

$$u_{it}(\mathbf{y}) = \underbrace{a_{it}y_{it} - \frac{1}{2}y_{it}^2}_{\text{Benefits - Cost}} + \underbrace{\beta\Big(\sum_{j\neq i} g_{ij}^w y_{it}y_{jt}\Big)}_{\text{Social Component}}.$$

The first two elements represent the benefits and costs of criminal effort y_{it}, where $a_{it} > 0$ denotes differences in the individual's economic benefits from criminal activity and the cost of engaging in crime is given by $\frac{1}{2}y_{it}^2$, which increases with own effort.

The social component is included in the utility function by adding $\sum_{j\neq i} g_{ij}^w y_{it}y_{jt}$. The social component reflects the influence that the action or outcome (e.g., criminal activity) of other members of group g has on the utility of i. The social influence of i on j is captured by g_{ij}^w. The overall effect of the weighted sum of bilateral influences is captured by β. The idea behind this social component is that individuals derive more utility from committing a crime when their connections commit more crimes, which means that crime decisions are *complements*. Therefore, the parameter that we would like to estimate in the empirical section is β, which reflects the effect of the criminal records of the group, holding the other variables fixed.

In equilibrium, each individual maximizes their own utility by choosing a level of

[13] By definition, $g_{ij} = 0$ means that individual i is not connected to j and therefore does not have an influence on j. We can let $g_{ii} = 0$ and use an undirected network such that if $g_{ij} = 1$ then $g_{ji} = 1$.

criminal effort. The first-order condition for each individual i is

$$y_{it} = a_{it} + \beta \sum_{j \neq i} g_{ij}^{w} y_{jt}. \tag{1}$$

Thus, the level of crime that an individual will show in equilibrium is determined by their own economic characteristics, a_{it}, and by the individual i's weighted sum of their group's criminal efforts, $\sum_{j \neq i} g_{ij}^{w} y_{jt}$. Therefore, the first-order condition can also be divided into individual-level and social-level elements. On the one hand, suppose that the personal cost-benefit element, a_{it}, is subject to variation in measured and unmeasured factors:

$$a_{it} = x_{it}\eta + \alpha_g + \tau_t + \epsilon_{igt},$$

where x_{it} are the observed variables that explain variation in the individual cost-benefit ratio, α_g and τ_t denote the full set of group and year effects, and ϵ_{igt} represents the unobserved heterogeneity. On the other hand, in the second element of the best response, the social component, suppose that the scaled weights g_{ij}^{w} follow

$$g_{ij}^{w} = \begin{cases} 0 & \text{if } \ g_{ij} = 0, \\ \frac{1}{\sum_{j \neq i} g_{ij}} & \text{if } \ g_{ij} = 1. \end{cases}$$

Thus, $\sum_{j \neq i} g_{ij}^{w} y_{jt}$ in the best response is the average of the criminal record of the agents who influence individual i in g. This parametrization, known as the *linear-in-means*, determines that the criminal effort of i depends linearly on the mean of the criminal records of the other members of the group, $E[y_{it}]$. As a consequence, what we can study is the effect of the 'average level of criminality of the group.' For example, an individual with one connection who commits two crimes is affected to the same degree as an individual with two connections who each commit two crimes.

Following Kline and Tamer (2020), the elements that affect an individual's equilibrium best response in Equation 1 can be represented in its corresponding empirical equation:

$$y_{it} = x_{it}\eta + E_{gt}[y_{it}]\beta + \alpha_g + \tau_t + \epsilon_{igt}. \tag{2}$$

Because the outcomes, y_{it}, are simultaneously determined in Equation 2, the previous equation cannot simply be estimated in a regression. The aim of the following sections is to capture the effect of local economic conditions, η, separately from the effect of the peers' criminal activity, β. To that end, the following sections describe the structure of the data I use as a proxy for the variables in the model and the identification strategy.

Data

Data for this project come from three different sources. The first data set—gold mining data—provides the tools to create the treatment variable. I interact the time-series variation in the international price of gold with information on illegal gold production at the municipality level. The second data set—conflict experience—provides individual-level information, which serves as the basis for the construction of the network of wartime connections. The third data set—criminality—provides individual-year-level information of captures of ex-combatants after demobilization.

Gold mining data

The geographic variation in illegal gold productions is drawn from the mining census published by the Colombian Ministry of Mines and Energy in 2010. The census contains records of the number of illegally mined gold deposits in each municipality prior to 2009. Municipalities are the lowest level of disaggregation in the census. Furthermore, because the geographical measure of gold production is defined before the period of analysis of this paper and the expansion of Colombia's illegal gold mining industry, the records do not reflect potentially endogenous production efforts correlated with the main outcomes over the period of analysis. The census was carried out in more than 600 municipalities that reflect the places that, due to geographical characteristics, the government identified as potential producers (see Figure A.6). The census counts the number of mines without permits in each municipality and the variable changes from 0 to 254, with the activity concentrated in the Caribbean and Andean regions. Information about other municipal-level characteristics comes from the National Department of Statistics (DANE), the municipal panel from the Centro de Estudios sobre Desarollo Economico (CEDE) of the Universidad de los Andes, and data collected by Acemoglu, Garcia-Jimeno and Robinson (2015) and Dube and Vargas (2013).

The other identifying source of variation comes from changes in the international price of gold from 2013 to 2016. The data on the international price of gold and other commodities were obtained from the World Bank Global Economic Monitor Commodities Database. Importantly, Colombia is not an international price maker in the gold market, so variations in the price of gold experienced during the period studied can be arguably considered exogenous to local production (Dube and Vargas, 2013).

Conflict experience

I use two different sources to create the wartime network measure. The first is a census of ex-combatants conducted by the Colombian Agency of Reintegration (Agencia Colombiana para la Reincorporación y la Normalización, ARN) as part of the reintegration process. The survey contains information concerning the population of paramilitary members who initially demobilized. It also includes information about the subunit inside the larger structure of the paramilitary organization to which each ex-combatant belonged during the conflict, which enables me to identify which individual belonged to which subunit. the list of units is shown in figure A.3. The paramilitary organization AUC had 41 subunits at the time of demobilization.

Second, to capture the rank of each ex-combatant during the conflict, I use information from a survey conducted by ARN and the International Organization for Migration (OIM) about conflict experience. The survey includes questions about the rank inside the organization of 16,761 paramilitary ex-combatants. The ranks mentioned in the survey vary from commander to foot soldier. The survey, known as Base Line (Línea Base), was implemented for several months beginning in 2007 and is one of the most comprehensive data sets about ex-combatant experience. Figure A.3 also shows the recognized subunits, the ranks/positions identified by the agency, and the number of members in each wartime group.

Using both sources of information, I construct the links between all the individuals in my sample. Two individuals are considered to be linked if they were of the same rank and served in the same subunit for at least one year during the conflict. This way of capturing wartime connections is based on interviews and ex-combatants' recollections about the most important connections during the conflict.

The representation of the network resembles the 'military squads network' in basic network classifications (Christakis and Fowler, 2009), in which the group is described as having a transitive relationship in which all those involved know each other. I provide additional justification for this selection with qualitative and survey evidence in section K of the appendix and consider variations of the wartime connection definition in the empirical analysis. The section contains a complete description of the original survey with ex-combatants about wartime connections.

There are a total of 559 groups/networks in the sample. The average group has approximately 30 members. The smallest group is comprised of 1 individual and the largest has 1110 individuals. The median group has a size of 4 and there are only 12 groups with more than 300 people.

Additionally, it is important to highlight that ex-combatants are spread all over the country. In other words, ex-combatants have several wartime peers living outside their own municipality. The empirical analysis includes different versions of the network definition, including only subunit membership and time spent together during the conflict.

Criminality

In order to examine whether ex-combatants exposed to changes in returns to illegal activities are more likely to engage in crime, I use confidential and anonymized information from the National Police of Colombia on the universe of ex-combatants captured in the period 2013 to 2016. I use an indicator of whether an ex-combatant was captured for a crime during the period of study along with the type, location, and date of the last crime this person committed. There are two categories of captures reported in the data: captures as a result of an investigation (labelled *Capture* in the analysis) and captures in flagrante (labelled *Red-handed capture* in the analysis). Figure A.1 displays the distribution of crimes among ex-combatants across Colombia and figure 1 shows the types of crimes for which ex-combatants were arrested according to the articles of Colombia's penal code.

I do not rely on perceptions, opinions, or self-reported participation in criminal activities, and instead use a behavioral indicator. This is the best available information, because it is used to measure individual-level criminal behavior—it is used in all other studies about postconflict criminality. However, there are some concerns that are worth discussing. One is that captures reflect law enforcement capacity and the results may reflect the contagion of 'law enforcement capacity' instead of contagion of crime. To minimize this concern, the main analysis focuses on in flagrante captures, because these captures are less dependent on police investigation and may be carried out by citizens.[14]. I discuss other possible concerns associated with this measurement in light of the results in a separate section in the appendix.

I provide a list of all the variables used in the paper and identify their source in the replication materials (Vásquez-Cortés, 2023). When data is restricted, I explain how other researchers can request it.

[14] Article 32 of the Political Constitution of Colombia establishes that an offender who is caught in flagrante delicto, that is, while committing a crime, can be apprehended either by the authorities or by a private citizen

Identification

Recall that the identification problem arises from the presence of y_{it} on both sides of Equation 2. Following (Manski, 1993, p. 534) and provided that $\beta \neq 1$,, we can define the social equilibrium by considering the expectation on both sides of Equation 2:

$$E_{gt}[y_{it}] = E_{gt}[x_{it}]\frac{\eta}{1-\beta} + \frac{\alpha_g}{1-\beta} + \frac{\tau_t}{1-\beta}. \tag{3}$$

Suppose that this equilibrium holds for the observed data in each period t. Then, substituting Equation 3 back into the individual-level model in Equation 2, we have

$$y_{it} = E_{gt}[x_{it}]\theta + x_{it}\eta + \alpha_g^* + \tau_t^* + \epsilon_{igt}, \tag{4}$$

where $\theta = \beta\eta/(1-\beta)$. The first element of Equation 4 estimates the mean of the economic change for members of the group, the second element estimates the variation in the economic returns for each individual, and α_g^* and τ_t^* are the rescaled group and time effects, respectively.

If we can (1) identify coefficients on $E_{gt}[x_{igt}]$ and x_{igt} and (2) partial out the group and time effects, then we can back out β, which is the social interaction parameter of interest:

$$\hat{\beta} = \frac{\hat{\theta}}{\hat{\theta} + \hat{\eta}}. \tag{5}$$

The conditions that are sufficient to identify β are the following: first, to identify coefficients on $E_{gt}[x_{it}]$ and x_{it}, we need that $E_{gt}[x_{it}]$ and x_{it} not be confounded with respect to ϵ_{igt}. We also need that $E_{gt}[x_{igt}]$ and x_{igt} not be perfectly collinear. We obtain this with the variation in x_{igt}, which is equivalent to the effect of each shock *within* the groups indexed by g.

In other words, β will capture the effect on criminality of the criminal activity of peers who were affected by the exogenous economic variation by transforming the coefficients of the individual- and group-level estimations.

The treatment variable for the individual-level effect, x_{igt}, is the price of the commodity interacted with the intensity of its production in the municipality of residence of i in year t. In the case of gold, the shock is the interaction of the international price of gold with the number of illegal gold mines in the municipality. The outcome of interest, y_{it}, measures the number of red-handed captures of individual i in year t:

$$y_{it} = \underbrace{E_{gt}[(Price_t \times Intensity_{ig})]}_{\text{Mean Group Schok}_{gt}} \theta + \underbrace{(Price_t \times Intensity_{ig})}_{\text{Price Shock}_{it}} \eta + \alpha_g^* + \tau_t^* + \epsilon_{igt}, \quad (6)$$

To partial out the group and time effects, I take advantage of the panel data and include group (α_g^*) and time (τ_t^*) fixed effects. For reasons of robustness with fixed effects models, I use ordinary least squares to estimate the parameters and then the delta method for inference on $\hat{\beta}$. That is, to estimate the peer effects, β, I compute the estimates and standard errors for the composite parameters estimated in the main specification in Equation 6. I cluster standard errors at the group level and provide additional results with individual and municipality clustered standard errors.

In addition to estimating the parameters of the model, I conduct several robustness checks to address potential concerns. First, in all estimations I include municipality fixed effects. By including these fixed effects, I control for invariant differences between gold- and non-gold-producing municipalities. Second, I include time trends to control for changes in aggregate time trends across years. Third, I include region time trends and municipality-specific time trends for a set of baseline characteristics.[15] These interactions are included to control for potential differential changes across types of municipalities. More importantly, the municipal-level variables related to mobility and connectivity (distance to Bogotá and paved primary roads) enable me to control for any potential biases coming from differential trends in districts that have greater economic needs or are potentially more connected. Finally, I include a set of individual-level characteristics (age, gender, and race).

[15] Colombia is divided into five regions. I include municipality-specific baseline time trends for poverty index, total population, distance to local market, km of paved primary roads, and distance to Bogotá.

Results

In this section, I present the main results. First, I provide evidence that ex-combatant criminal records are significantly affected not only by their local economic conditions, but also by their wartime peers' average criminal activity. I complement these main results in two ways. First, I consider the effect for different levels of the strength of the wartime connection. I look at the size and precision of the peer effects for connections that range in duration from one to five years during the conflict. Second, I examine the elements driving the peer effects by showing results for collective and individual crimes separately. I show that peer effects are mostly driven by the effect on collective crimes.

Economic and Peer Effects

Panel A of Table 1 shows the estimation of the parameters in Equation 6 and panel B shows the estimation of the peer effects following the transformation in Equation 5. The shocks have been standardized across all estimations. All columns include group, time, and municipality fixed effects. Results show that higher economic returns for illegal activities are positively associated with an increase in criminality. The coefficient on the individual economic changes in column 1, reflecting variation in local economic returns to illegal markets, shows that a one standard deviation increase in the treatment is associated with an increase between 0.372 and 0.394 red-handed captures, depending on the specification. The main results are consistent with the theoretical expectations and other studies about commodity prices shocks and crime.

The most important result is the robust, positive, and significant effect of peers' criminal activity on the likelihood that an ex-combatant will be captured. Column 1 of panel B shows the coefficient associated with the peer effects from the theoretical model. There is a significant effect of wartime peers' criminality on individual criminal activity. A one standard deviation increase in the average criminal activity of an ex-combatant's group increases the ex-combatant's criminal record between 0.394

Table 1: Effect of Gold-price Shock and Effect of Peers Criminality—Red-handed Captures

	Red-handed captures				
	(1)	(2)	(3)	(4)	(5)
Panel A: Economic shock and average shock for the group					
Economic Shock	0.393***	0.394***	0.372***	0.379***	0.380***
	(0.0881)	(0.0882)	(0.0885)	(0.0932)	(0.0932)
Average Shock	0.256**	0.256**	0.275**	0.289**	0.286**
	(0.104)	(0.104)	(0.107)	(0.114)	(0.114)
Panel B: Criminal peer effects					
Peer Effect	0.394***	0.394***	0.425***	0.433***	0.430***
	(0.125)	(0.125)	(0.127)	(0.134)	(0.135)
Mean of Outcome	0.0242	0.0242	0.0244	0.0243	0.0244
S.D. of Outcome	0.1697	0.1697	0.1703	0.1704	0.1704
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

Note: The dependent variable includes only red-handed arrests for the 2013—2016 period. Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. The economic shock is defined as the interaction of the natural logarithm of the international price of gold and illegal gold production, in standard deviations. Panel B shows the estimation in Equation 5, representing the effect of wartime peers' arrests on $i's$ criminality. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and km of paved primary roads. Individual controls include age, gender (female), and race (indigenous and afro). *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level. Complete model results included in Table A.23 in the supplementary material.

and 0.433 red-handed captures, depending on the specification. This estimate captures the effect of an increase in the average criminality of the wartime group as a result of economic changes in the groups' municipalities. Given that the peer effect reflects the impact of the actions of group members, the size of the impact depends both on each individuals' group characteristics (i.e. exposure to the shock at the group level) as well as to what is going in that individuals municipality (i.e the individual shock). Thus, the effect will change for individuals depending on where they reside, and their group characteristics. [16]

The results in table 1 are consistent across different specifications and robustness checks as explained in the identification section. The magnitude of the coefficients barely changes compared to the baseline estimation. Economic changes and peer effects remain similar when I include time trends, region- and municipality-specific time trends, and individual covariates. Column 3 includes the interaction of region and year; column 4 includes the interaction of municipality characteristics with year, which accounts for potential biases stemming from differential trends in places that may have been more affected by violence; and column 5 includes individual covariates. Complete model results for all results in the paper can be found in the online appendix as part of the replication mateorials.

Robustness

I address some potential concerns regarding the main identification strategy. First, I replicate the analysis with all types of captures, not only red-handed (Table A.2). Second, I exclude from the analysis groups with more than 500, 250, and 100 members (Table A.4). Third, I consider different measures of the treatment and sample, focusing on municipalities with low to no illegal gold production (Table A.5). All re-

[16] For example, for an individual who belonged to the group of foot soldiers of the Bloque Venecedores de Auraca, a group of about 340 members residing in several different municipalities, the change in the mean group shock between 2015 and 2016 amounts to an increase in criminality from 62 p.p. to 66 p.p. (depending on the specification) with respect to the mean criminality. On the other hand, the effect for an individual who was a foot soldiers in the Bloque Catatumbo, the change in the mean shock during the same period, amounts to an increase in criminality between 16 p.p and 17 p.p.

sults are consistent with the idea that local economic conditions and peers' activity affect recidivism after conflict.

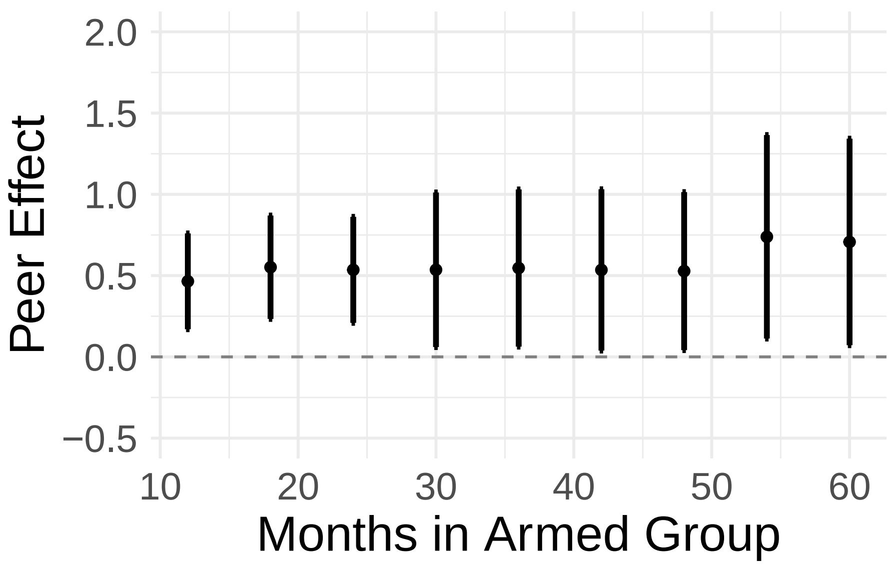
I perform additional tests that are included in the online appendix as part of the replication materials: I replicate the main analysis, clustering standard errors at the individual rather than the group level (Table A.8), I consider the effect of a change in the production levels of other legal commodities such as oil (Table A.11), I perform a falsification test with the leads of the treatment (Table A.12), and I look at the impact of the gold shock on ex-combatants' noncriminal activities (Table A.18).

In sum, a clear pattern emerges in which illegal markets and peers' activity play important roles in recidivism.

Strong and Weak Wartime Ties

The results should vary if we consider a definition of wartime network that affects the strength of the connection between peers. To address this possibility, I consider variations in the effects for arguably stronger and weaker links. The stronger ties refer to the time ex-combatants spent all together during the conflict: people who spent a long period of time together during the war may show differential peer effects than if they had spent a short period of time together. Figure 5 shows the peer effects for different wartime connections in which all members of the wartime network spent the same time together. The results show that when all members of the newly defined group spent more time together, the peer effect increases. The estimated peer effect coefficient for 1 year together in conflict is about 35% smaller than the one estimated for 4 and 5 years. These results are consistent with the central intuition. Nevertheless, the results are to be taken with some caution: time spent together is self-reported in months (which explains the concentration of observations every six months in the data). Additionally, the argument is that the collective experience of conflict essentially determines the bonds of war. Therefore, the strength of the relationship should only slightly change the effects we find. Importantly, more time spent together during the conflict could also imply that ex-combatants switched units and rose in rank during the war. While mobility was low, we should expect that more time in conflict was related with more time spent with peers.[17]

Figure 5: Peer Effect of Strong Ties: Time Together in Conflict



Note: Estimation of peer effects following Equations 6 and 5, considering groups in which all members were in the same armed unit between 1 and 5 years. Complete model results included in Table A.42 in the supplementary material.

We can also consider a definition of the network that incorporates weaker ties. In Figure A.5 I show that the peer effects are consistent if we define a weaker wartime connection in which two people belong to the same network because they belong to the same unit—regardless of rank. While the peer effects coefficient is positive, its magnitude shrinks compared to the other results with stronger ties (see Figure A.4).

Overall, although the results found by using different definitions of the wartime network show some slight change, the magnitude and relevance of the coefficients confirm the intuition behind each network: stronger ties are associated with a larger peer effect and weaker ties with a smaller peer effect. The effect that the criminal activity of an ex-combatant has on the criminal records of his wartime connections increases as the time spent in the same unit and rank during the war increases.

[17] Additional information from an original survey administered by the author in section K of the appendix shows that ex-combatants spent more time with other fighters in their unit and of the same rank than with any other combatant during the war.

Collective and Individual Crimes

In this section I study the effect of economic changes and peers' activity, separating the types of crime for which ex-combatants were captured. Table 2 shows the estimations of economic returns in panel A and the peer effects in panel B for *collective* crimes. In constructing this classification I follow Khanna et al. (2023), who rely on the Colombian National Police's categorization of gang-related crimes. The list with the classification is in table A.14 of the online appendix in the replication materials. Collective crimes include homicide, extortion, and organized crime/conspiracy, among others. Individual crimes include simple assault, sexual harassment, and use of false identification, among others.

The results show an increase in criminality as a result of the economic changes for collective crimes. Column 1 shows that a one standard deviation increase in the average criminality of the group is associated with around 0.3777 more collective crimes. Columns 2 through 5 replicate the additional specifications to address some of the potential concerns regarding the main identification strategy. The results are consistent across all of these tests.

Taken together, these results show that the criminality of wartime connections had a major impact on an ex-combatant's probability of being captured. The results are concentrated among collective crimes, which are the types of crimes that are most likely to be susceptible to changes in prices and illegal returns and, more importantly, to changes in the criminal activity of peers.

I subject the main estimates to additional tests. I briefly summarize these tests here and provide greater detail on each of them in the appendix and replication materials.

Measurement. An extensive discussion is devoted to measurement error in the appendix section G. I expand on the earlier discussion of the benefits and limitations of using capture as a proxy for crime.

Ex-combatant Mobility. In appendix section H, I show that the results are robust when I examine individuals who moved to a different municipality (Table A.6). The results rule out the possibility that the effects are driven by local enforcement in gold-

Table 2: Economic Shock and Peer Effects—Collective Crimes Only

	Red-handed captures for collective crimes				
	(1)	(2)	(3)	(4)	(5)
Panel A: Economic shock and average shock for the group					
Economic Shock	0.343***	0.344***	0.315***	0.279***	0.279***
	(0.0777)	(0.0777)	(0.0740)	(0.0776)	(0.0776)
Average Shock	0.167*	0.168*	0.188**	0.210**	0.208**
	(0.0867)	(0.0869)	(0.0894)	(0.0974)	(0.0971)
Panel B: Criminal peer effects					
Peer Effect	0.328**	0.328**	0.374***	0.429***	0.427***
	(0.139)	(0.139)	(0.140)	(0.155)	(0.155)
Mean of Outcome	0.0173	0.0242	0.0244	0.0243	0.0244
S.D. of Outcome	0.1458	0.1697	0.1703	0.1704	0.1704
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

Note: The dependent variable includes only red-handed arrests for collective crimes in the 2013–2016 period. Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. The economic shock is defined as the interaction of the natural logarithm of the international price of gold and illegal gold production in standard deviations. Panel B shows the estimation of Equation 5, representing the effect of wartime peers' arrests on $i's$ criminality. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pretreatment levels of poverty, population, distance to Bogotá, and km of paved primary roads. Individual controls include age, gender (female), and race (indigenous and afro). *** = significant at the 1% level, ** = significant at the 5% level, and * = significant at the 10% level. Complete model results included in Table A.24 of in the supplementary material.

producing areas.

Dyad Analysis. In appendix section I I conduct a dyad analysis, in which instead of considering the group-to-individual ($g - i$) effect, I rearrange the data to estimate the individual-to-individual ($i - j$) effect (see results in Table A.7).

Original Survey. Section K of the appendix presents the results of the analysis of an original survey with ex-combatants in Colombia to explain better the relevance of social networks (Figure A.9) and wartime peers in recidivism and reintegration processes (Figure A.10).

The following additional results are included in the online appendix as part of the replication material:

Placebo Network. I show that changes in gold price are not associated with variation in captures for a *placebo* network of ex-combatants (see Table A.9). That is, I show that it is not the case that a variation in the price of gold is associated with more captures for all other ex-combatants in all other municipalities, but only for those previously connected.

Economic Integration and Spatial Correlation. Given that some municipalities in Colombia are highly economically and socially integrated, it is essential to perform additional tests that consider mobility between municipalities, labor markets, and the spatial correlation of the economic shock (see Soifer (2019) for a broader discussion). Therefore, I show consistent results (Table A.13) correcting for spatial correlation following Conley (1999), and I include specifications with additional variables directly related to mobility and labor market conditions (Table A.19).

Nature of Collective Crimes. Additionally, table A.15 shows that all captures, not only red-handed, increase as a result of the economic shock. In this case, peer effects are also positive and comparable with other results, but are not significant. To complement this result, as a placebo test, table A.16 presents data showing that the economic shock does not have a significant effect on captures related only to individual crimes.

Non-Economic crimes. I present an additional discussion about the economic and collective nature of some crimes such as arms possession and homicide (Table A.17) and other non-economic crimes (Table A.18).

Centrality and other Individual Measures. I present a descriptive correlation of illegal gold production and crime (Table A.20), the relationship between crime and other individual-level variables including the ARN reintegration index (Figure A.11), education (Figure A.12), and centrality measures (Table A.21).

Historic Gold Production. To discuss the implications of the illegality of the commodity studied in the paper I show that there are no significant peer effects when we consider places where historically more gold, not only illegal, has been produced (Table A.22).

Discussion

The previous section showed that postconflict crime is influenced by changes in local economic conditions and peer effects. These results have implications regarding peace-transition activities.

It is important to underscore the relevance of the armed group's recruiting strategy and the demobilization process. On the one hand, several studies have shown that material incentives were indispensable for the paramilitaries (Nussio and Ugarriza, 2013; Gutiérrez Sanín, 2008). This element is vital to our argument because we focus on the impact of economic shocks. On the other hand, the collective demobilization of paramilitaries makes it possible to argue that ex-combatants may maintain links with former combatants after demobilization. The findings pin to demobilizations that occur collectively and not to those of people who abandon their military structures because they are no longer part of that criminal network. Deserters generally do not respond to wartime commanders or peers after demobilization. In fact, the behavior of FARC deserters is different in many respects (Oppenheim et al., 2015).

We can consider alternatives to reduce reliance on war networks in the aftermath of conflict. The first step is to estimate the effect of reducing dependency on criminal networks. What would be the effect, for example, of a policy that addresses war networks? To answer these questions, in section J of the appendix I perform a counterfactual analysis of the predicted values of captures when we reduce wartime connections. As expected, red-handed captures decrease as we reduce network dependency, regardless of economic changes.

However, what does it mean to mitigate criminal connections? The second step concerns strategies to reduce reliance on networks in wartime. Recent evidence on social contact interventions (Mousa, 2020; Lowe, 2021; Scacco and Warren, 2018, 2022) appears to suggest a promising avenue for this type of policy, through which participants can reduce their prejudices toward outgroups and, what is more important in this case, create new connections. Reducing criminal networks in the counterfactual experiment can also be interpreted as expanding noncriminal networks.

However, this analysis should not be taken as suggesting that all types of combatant connections should be broken. The expectation with such an intervention is that ex-combatants keep their friendships and political and social wartime networks unchanged. An individual can have different networks for different purposes; the results of the experiment point to economic connections, specifically new ones outside the former military structure, as potentially being able to promote reintegration.

Conclusions

This paper studies the social logic of recidivism among former members of illegal armed groups. I argue that the networks that combatants develop during conflict facilitate delinquent behavior after demobilization. Given the time spent in military life, ex-combatants may rely on wartime connections in relation to many different activities. These connections are not necessarily the primary ties that they hold as civilians, being mostly weak ties, but these ties do help them to find out about economic, job, and crime opportunities. Therefore, ex-combatants are likely to be affected by the behavior of these connections.

I show that changes in the economic returns to criminal activity increase the participation of not only the ex-combatants directly affected by the local economic changes, but also that of their peers during conflict. Contrary to previous studies of Colombian ex-combatants, I consider the local and external conditions that could affect the decision of ex-combatatants to participate in crime. In doing so, I study only one group, the paramilitary members, and how their reintegration process was interconnected with the illegal gold-mining industry.

This study highlights the relevance of weak ties for criminal behavior in general and for ex-combatants in particular. However, it is important to note that networks can also play a positive role in the reintegration process. Support networks and political networks, for example, could potentially facilitate reincorporation into civilian life. The fact that some wartime networks, as shown in this paper, affect recidivism suggests that the composition, type, and strength of networks should be carefully addressed in postconflict initiatives.

Future research could explore the mechanisms that explain why wartime connections are related to participation in criminal activities. Potential explanations include peer pressure, social status, and responsibility diffusion. All these channels could be studied with a survey that captures the relevance of these factors and further evidence on the effects of wartime connections after peace agreements.

[On human subjects] The author declares the human subjects research in this article was reviewed and approved by New York University and certificate numbers are provided in the appendix. The author affirms that this article adheres to the APSA's Principles and Guidance on Human Subject Research.

[On data transparency] Limitations on data availability are discussed in the text and appendix. Research documentation and available data that support the findings of this study are openly available in the APSR Dataverse at (Vásquez-Cortés, 2023).

[On ethics & conflicts of interest] The author declares no ethical issues or conflicts of interest in this research.

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Main Appendix for “Peer Effects and Recidivism: Wartime Connections and Criminality among Colombian Ex-combatants"

by Mateo Vásquez-Cortés

List of Tables

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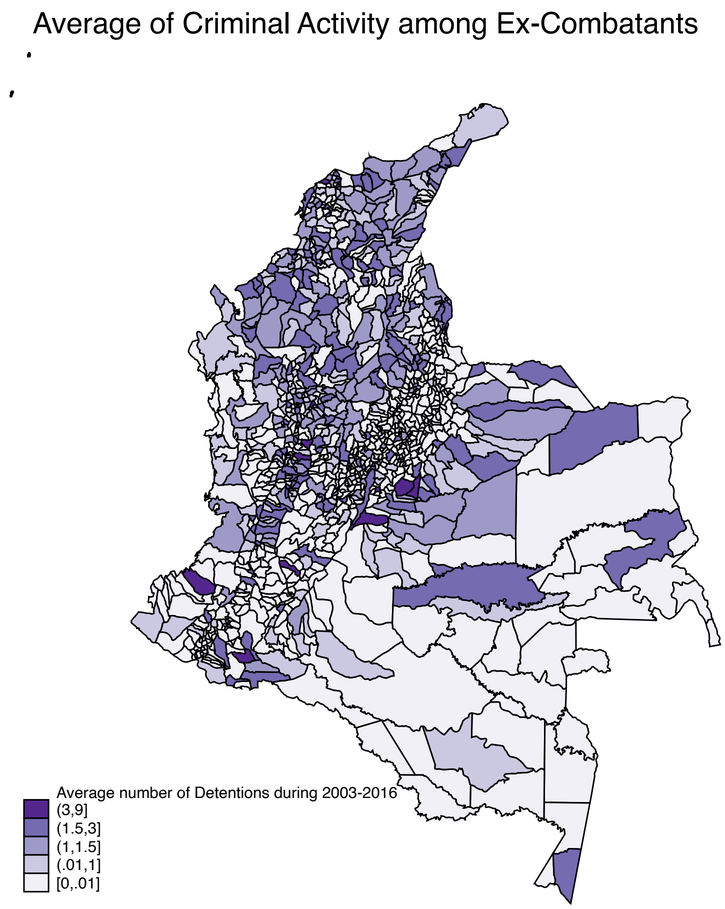
A Descriptive Statistics

In this section, I present descriptive statistics, the geographic distribution of ex-combatants criminal activity, the density of arrests, and the composition of the wartime networks following the parameters explained in the document.

Figure A 1: Ex-combatants' Captures



The map shows the location of the total number of captures from 2003, the moment of demobilization, to 2016 by ex-combatants in the place where they were captured..

Table A 1: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.
Panel Variables			
Number of arrests	50,162	0.037	0.21
Number of flagrant arrests	50,162	0.024	0.17
Municipal Variables			
Number of illegal gold mines	337	17.852	36.713
Length of oil pipe lines, km	588	0.107	0.333
Annual Variables			
Log global gold price, USD per ounce	4	7.151	0.191
Log global oil price, USD per barrel	4	4.082	0 .440
Ex-combatant Variables			
Age	16,771	37.4	7.45
Children	13,268	1.05	1.25
Socioeconomic stratum	16,403	1.34	0.63
Age joined armed group	16,762	24.24	7.66
Months in armed group	16,771	39.49	33.47
Years of education	16,446	9.189	3.66

Figure A 2: Densities of Arrest Rates across Colombian Municipalities

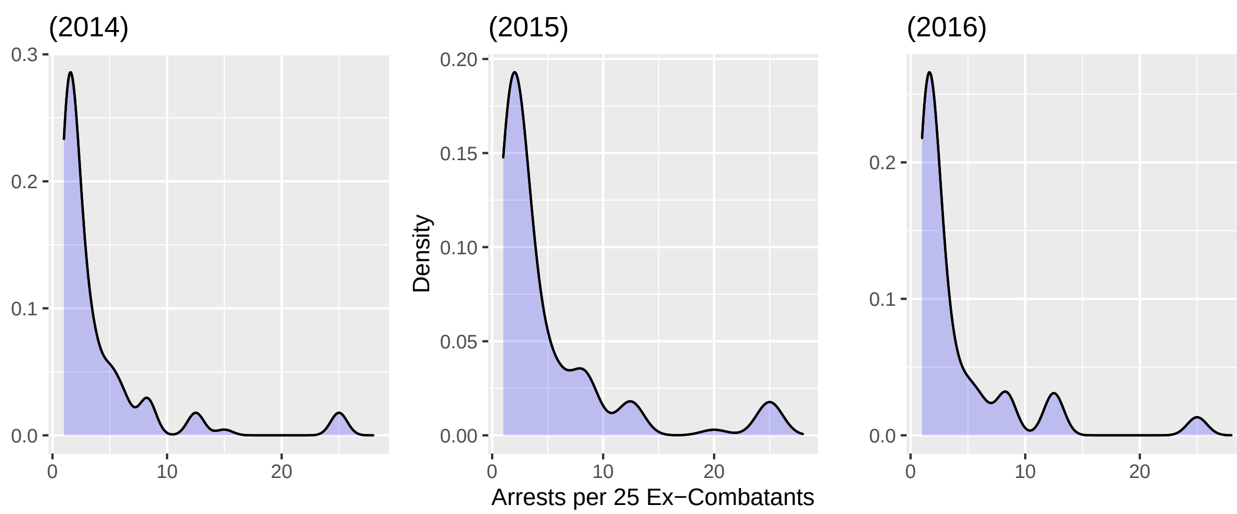
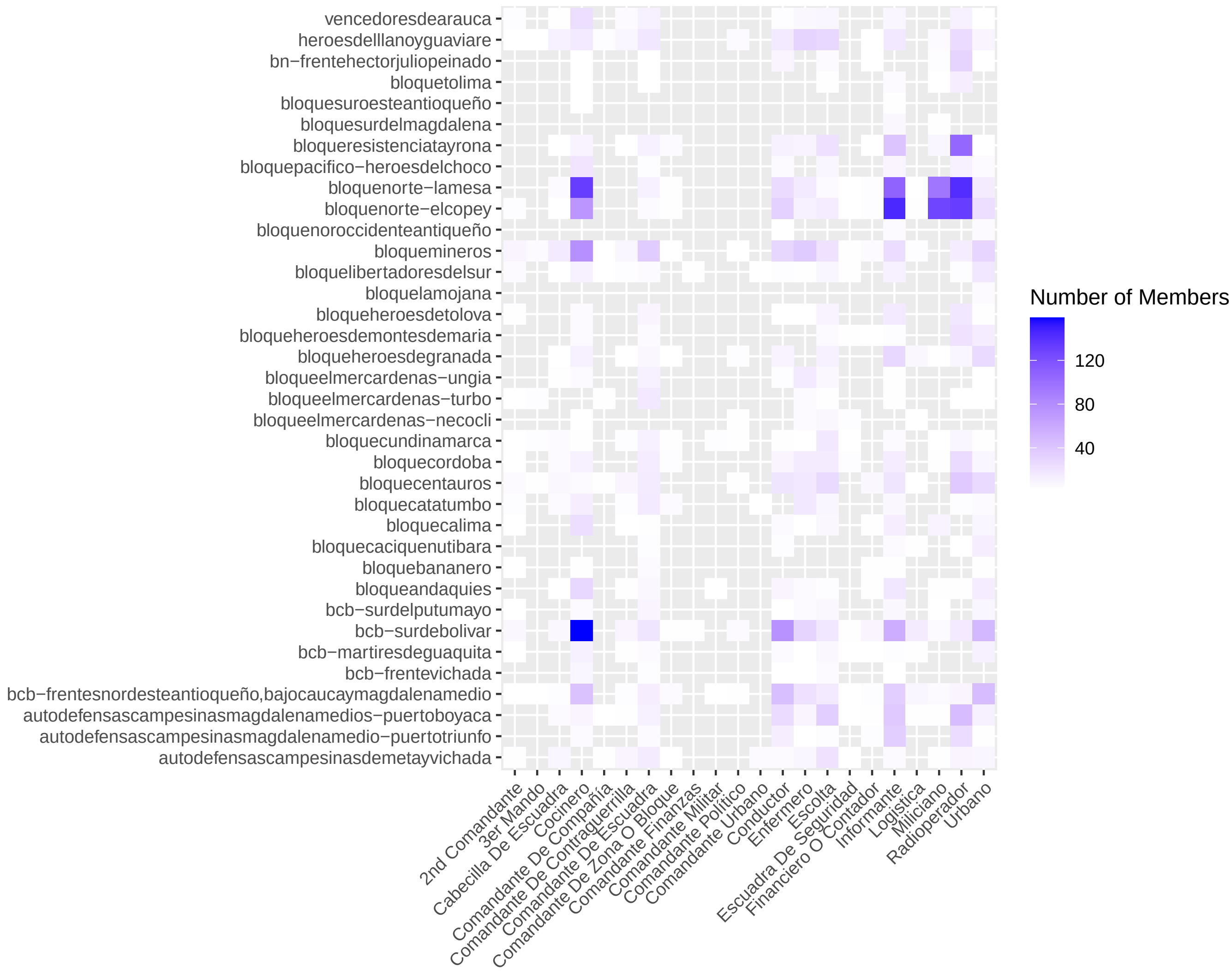


Figure A 3: Units, Ranks (In Spanish), and Number of Members in Wartime Groups



The figure shows the units that composed the AUC and the positions inside the units as self-identified by the former combatants and classified by the ARN. The figure excludes the position "Patrullero" (foot soldier) for visualization purposes, since it encompasses the few large groups of over 1,000 members.

B Main Results with All Captures

The following table presents the main results with all captures, and not only red-handed captures.

Table A 2: Effect of Gold Shock and Effect of Peers' Criminality – All Captures

	Captures				
	(1)	(2)	(3)	(4)	(5)
Panel A: Economic shock and average shock for the group					
Economic Shock	0.398***	0.398***	0.327***	0.319**	0.320**
	(0.121)	(0.121)	(0.120)	(0.128)	(0.128)
Average Shock	0.209*	0.209*	0.225**	0.251**	0.247**
	(0.113)	(0.113)	(0.110)	(0.115)	(0.115)
Panel B: Criminal peer effects					
Peer Effect	0.344**	0.344**	0.408**	0.440**	0.436**
	(0.170)	(0.170)	(0.178)	(0.183)	(0.184)
Mean of Outcome	0.0368	0.0368	0.0368	0.0367	0.0367
S.D. of Outcome	0.2071	0.2071	0.2072	0.2071	0.2072
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region $\times$ Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

The dependent variable includes all ex-combatant captures for the 2013-2016 period. Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. Panel B shows the estimation using Equation 5. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.25 of supplementary material.

All the complete model result for the tables and figures in this appendix can be found in the dataverse: (Vásquez-Cortés, 2023).

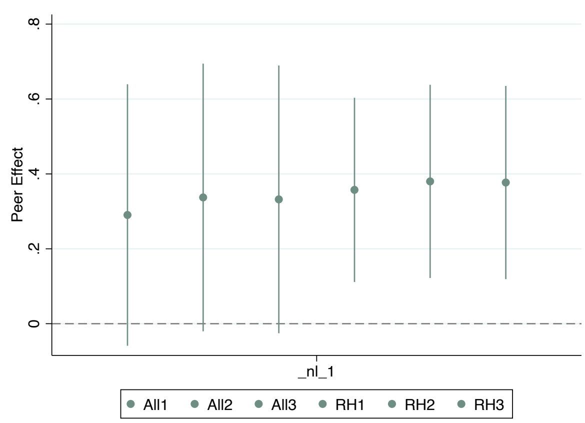
C Additional Results with Strong and Weak Ties

Figure A.4 replicates Figure 5 in main text without municipal and individual level controls (group, municipal and time fixed effects included) for comparison with weak ties results (Figure A.5).

Figure A 4: Peer Effect of Strong Ties: Years Together in Conflict

Estimation of peer effects considering only groups in which all members were in the armed group between one and five years. Full model results Table A.42.

Figure A 5: Peer Effect Weak Ties for All and Rend Handed Captures

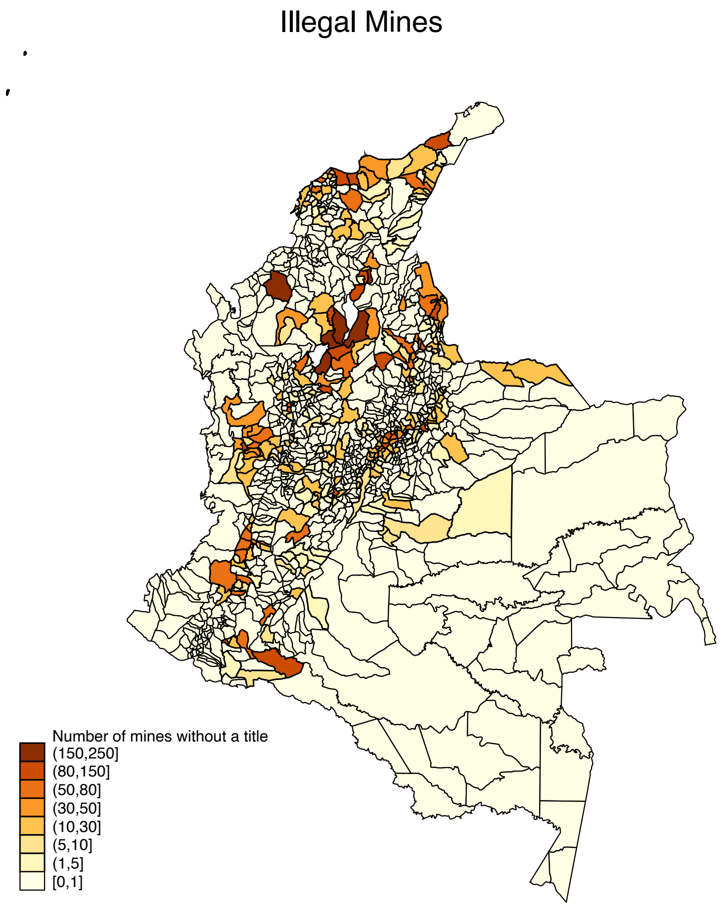


Estimation of peer effects with weak ties (unit in conflict only). Peer effects reflect the estimation of peer effect including different controls for all captures (All) and reda handed captures (RH): (1) includes group, municipal, and time fixed effects, (2) adds Region * time fixed effects and municipality conditions * time fixed effect, and (3) adds individual controls. Complete model results in Table A.43 of supplementary material.

D Gold Production Map

The following map shows the geographic distribution of illegal gold production, following the main text's explanation.

Figure A 6: Geographical Distribution of Oil and Illegal Gold Production



E Additional Details of Illegal Mining and Crime in Colombia

Here I expand on the context section concerning the context of illegal gold mining in Colombia. First, I argue that variations in the price of gold are related with violence. Second, I refer to several cases documented by journalists and qualitative studies on this relationship in Colombia.

Illegal mining is a significant source of revenue for poor and marginalized people and has significant effects on development indicators at the local level (Ibáñez and Laverde, 2014; Romero and Saavedra, 2016). Idrobo, Mejía and Tribin (2014) show that variations in the international price of gold caused a statistically significant increase in the homicide rate and the number of victims of massacre in municipalities with illegal gold mines. To complement this analysis, I explore (i) the differences between ex-combatant criminality versus overall criminality; (ii) the effect of the economic shock on national levels of criminality as measured by captures; and (iii) the relationship between general captures and other measures of crime and violence.

E.1 Ex-combatants' Criminality and National Crime Level

Figure A.7 compares ex-combatant's type of crimes with national levels. The graph shows the percentage of each type of crime for the ex-combatant population — as in Figure 1 — and the corresponding national-level percentage for each type of crime. For example, if we consider homicide, the fifth category in the graph, we see that 10% of the captures of ex-combatants in this period were related to that crime, and around 2.5% of captures at the national level were. One of the most important differences between the percentages by type of crime refers to organized crime (*'concierto para delinquir'*): while this crime alone captures 20% of ex-combatant captures, it represents less than 2.5% of the national captures. This is in line with the social logic of crime, in which ex-combatants would be involved in more collective crimes.

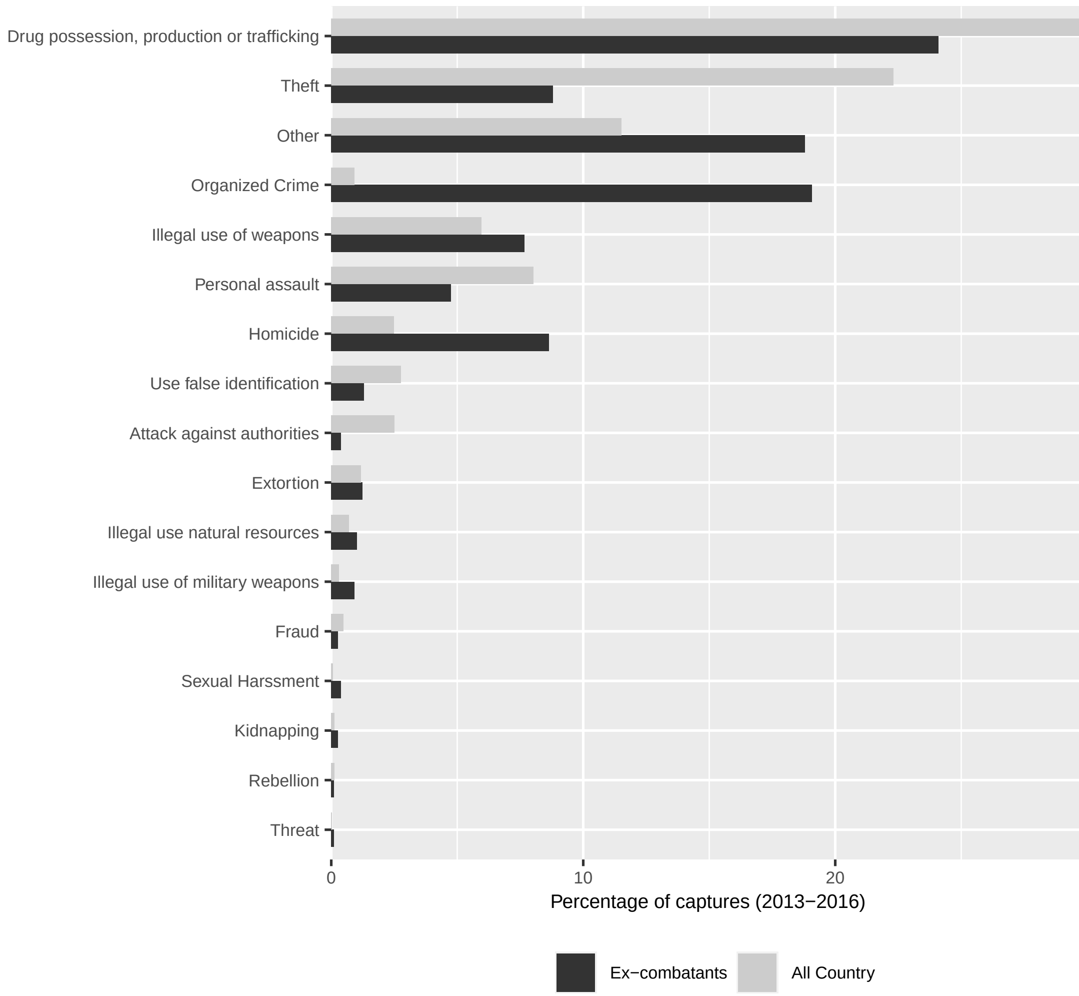
E.2 Economic Shocks and National-Level Captures

To look at the effect of the gold shock on overall levels of criminality and not only that of former paramilitaries, I estimate the following model:

$$y_{jt} = \alpha_j + \gamma_t + X_{jt} + \beta(\text{Gold}_j \times \text{GP}_t) + \epsilon_{jt}], \tag{7}$$

where y_{it} are crime outcomes including captures by the national police and captures of criminal bands (known in Colombia as Bandas Criminales, BACRIM) in municipality j and year t; α_j are municipality fixed effects; γ_t are year fixed effects; and X_{jt} are time-varying municipality controls that include log of population to account for the scale effect, because the dependent variable is measured as the number of captures. $Gold_j$ is the number of illegal gold mines in municipality j before 2013; GP_t is the natural log of the international price of gold in year t. In the equation, β captures the differential effect of the gold price on crime in municipalities producing more gold.

Figure A 7: Ex-combatant Crime and National Crime



Percentage of captures by type of crime for ex-combatants and national levels. Type of captures shown are the one present in both datasets.

In all specifications, I cluster the standard errors at the region level to control for potential correlation over time across municipalities within a region. Table A.3 shows the effect of the gold shock on captures for the 2013—2016 period. The coefficients in columns (1) and (2) show the effect of the gold shock on captures and those in columns (3) and (4) for criminal bands (BACRIM). The gold shock is positively correlated with captures and criminal band captures; though the estimates are of economic significance, they are of small statistical significance. This fairly stringent test provides some evidence that the the gold shock may affect crime and complements the results of Idrobo, Mejía and Tribin (2014), who show that the gold shock was particularly relevant in explaining levels of homicide and attacks in gold-producing areas for a different period.

Table A 3: Economic Shock at the National Level

	(1) National Captures	(2) National Captures	(3) BACRIM Captures	(4) BACRIM Captures
Municipal Gold Shock	4.716**	1.911	0.209**	0.145
	(2.058)	(2.379)	(0.101)	(0.113)
Mean of Outcome	1.9572	1.9572	0.0213	0.0213
S.D. of Outcome	1.9928	1.9928	0.0715	0.0715
Observations	1,164	1,164	603	603
Municipality FE	✓	✓	✓	✓
Year FE		✓		✓
Sample period	2013—2016	2013—2016	2013—2015	2013—2015

Dependent variables in columns 1 and 2 include all national-level captures from 2013 to 2016. Estimation based on Equation 7. Dependent variable in columns 3 and 4 include captures of criminal bands until 2015 (data constrained). Standard errors in parentheses clustered at the municipality level. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level.

E.3 Crime Chain across Municipalities

A key part of the argument is the systematic spread of crime across different locations. To complement the results presented in the main analysis, here I report some activities related to illegal gold mining that involve the participation of multiple actors in different locations. The infromation is based on new articles of captures of members of criminal organizations, many of which were created from former paramilitary units.

The gold value chain has several stages, including the production, stockpiling, buying and selling, and finally marketing (Ortiz-Riomalo and Rettberg, 2018). In each of these stages, the participation of several actors is necessary. In the production phase, for example, the machinery needed for gold extraction uses motor fuel oil that must be acquired and transported to the place of extraction. On many occasions, the input is obtained through local gas stations that request exaggerated amounts of motor fuel oil from other municipalities, for which they have to get approval from the local government. The national police director has stated that the process is complicated because the motor fuel oil is not illegal. What is illegal is the whole process that has to be carried out through intimidation and corruption in different places in order to transport the oil (Rubiano, 2017).

Something similar happens with machinery. According to the investigations of the General Prosecutor's Office and the National Police, the machines used for the exploitation of mines are generally built from parts of used machines that can be obtained in black markets in urban centers including Bogotá and Medellín. For the General Prosecutor, the 'capacity' of the machines to travel across the country without being detected is surprising — "you even get parts for machines that arrive from other countries, like Brazil" (Rubiano, 2017). Again, the process shows how illegal mining requires the participation of various agents in different places.

Finally, and very important, marketing involves purchasing by different suppliers in different parts of the country. The deposits of Antioquia, Córdoba, and Choó (the northeast of the country: the portion of Map A.6 where illegal mining production is concentrated) have commercial links, evidenced by payments to suppliers in places as far away as indigenous reservations in Guainía (the southwest of the country, non-gold-producing locations) (Semana-Sostenible, 2019).

E.4 Former Paramilitary Criminal Organizations

Many reports indicate that crimes throughout Colombia were carried out by organizations that were formed from units of the AUC. Illegal mining activities took a central role only after the demobilization of the paramilitaries. Before, other activities, such as cocaine trafficking, played a more important role. The report by Fundacion Ideas para la Paz (2017) shows the areas of influence of the criminal organizations recognized by the government as 'Criminal Bands' that have their origins in former AUC subunits. National and local newspapers, as I show below, usually report the capture of members of these organizations. The reports often mention activities in several municipalities and the link to illegal gold mining. For example, different reports document the capture of several members of the criminal organization Clan del Golfo, created from former AUC paramilitary unit Bloque Central, for illegal mining among other crimes, in several municipalities in Córdoba and Antioquia (Canal Monteria, 2019). The case of Montería in Córdoba is particularly important in explaining the results of this paper. Even today, the organization has operations across the country. The activities of members of the Clan del Golfo include organized crime, extortion, drug trafficking, and homicide (Monteia Radio 38, 2020) and the centers of operations are in Antioquia and Cordoba, where the 'Gold Tsar', who had funded illegal groups since 2012, was recently captured (Monteria Radio 38, 2019).

Another report mentions a series of arrests for extortion of members of a group that formed from another AUC unit, the Bloque Norte, in different municipalities of Magdalena (Semana-Region, 2015). The group consolidated in the study period (as of 2013), and operates in different parts of department of Magdalena and La Guajira in the northen part of the country (Caracol Noticias, 2002). According to news reports, their activities include organized crime, homicide, theft, and extortion, mostly of tourist organizations. These forms of criminal organizations and activities continue today in the same region (Diario Magdalena, 2020).

Finally, a group known as Los Puntilleros, who operate mostly in the western part of the country, has its origin in the former AUC unit of Heores del Llano y Guaviare. This group is engaged in a wide range of criminal activities in the area. Their expansion and growth process took place through intensive work to form agreements and alliances in which the organization incorporated former members of the AUC (InSight Crime, 2020). The group of Los Puntilleros actually make up a complex criminal network that have territorial influence in several locations where they control the population and regulate various activities, both illegal and legal (Diario Extra Llano, 2020).

The reports mostly confirm the argument made in this paper that criminal operations in different locations in the country were in many cases directly linked to the main source of revenue for criminal organizations in the period under study, illegal gold mining, and were related to criminal structures that emerged from former units of the AUC.

F Different Samples

To take into account the fact that some groups are very large and may be explaining the peer effect results, I exclude groups with more than 500, 250, and 100 members from the analysis, respectively, and obtain consistent results for the economic and peer effects as shown in table A.4 .

Table A 4: Analysis Excluding Larger Groups

	Red-handed Captures			
	(1)	(2)	(3)	(3)
	> 1,000 Members	> 500 Members	> 250 Members	> 100 Members
Panel A: Economic shock and average shock for the group				
Economic Shock	0.379***	0.244	0.0897	-0.016
	(0.108)	(0.169)	(0.198)	(0.221)
Average Shock	0.262**	0.290*	0.410**	0.432*
	(0.129)	(0.163)	(0.193)	(0.235)
Panel B: Criminal peer effects				
Peer Effect	0.409**	0.543**	0.820**	1.038*
	(0.159)	(0.271)	(0.359)	(0.540)
Mean of Outcome	0.0240	0.0233	0.0224	0.0198
S.D. of Outcome	0.1689	0.1671	0.1648	0.1509
Observations	32,990	21,608	16,309	11,837
Municipality, Year, and Group FE	✓	✓	✓	✓
Time Trends	✓	✓	✓	✓
Region × Year	✓	✓	✓	✓
Municipality Characteristics TT	✓	✓	✓	✓

Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. The economic shock is defined as the interaction of the natural logarithm of the international price of gold and illegal gold intensity prior to the study period. Panel B shows the estimation explained in Equation 5, representing the effect of wartime peers' arrests on $i's$ criminality. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.26 of supplementary material.

Additionally, I consider different measures of the treatment. The preferred specification is based on the intensity of illegal gold production in the municipality. To determine whether there are peer effects across all municipalities, we should expect the results to hold for individuals residing in places with low to no production, but with connections in gold-producing municipalities. Table A.5 shows that, with some variations, the results are consistent for individuals residing in municipalities with different levels of gold production. In all cases, crime is positively related with the economic variation for wartime peers.

G Measurement

The discussion about measurement is worth mentioning in light of the main results of the paper. Previous research on criminal peers has predominately relied on respondents' assessments of their own criminal records and their assessments of their peers'

Table A 5: The Effect of the Economic Shock for Different Levels of Gold Production

	Production below Mean (1)	Production below 25 Percentile (2)	No Gold Production (3)
		Red-Handed Captures	
Average Shock	0.339***	0.255**	0.303
	(0.104)	(0.109)	(0.291)
Mean of Outcome	0.0234	0.0231	0.0168
S.D. of Outcome	0.1668	0.1654	0.1332
Observations	26,499	22,765	4,825
Municipality, Year, and Group FE	✓	✓	✓
Time Trends	✓	✓	✓
Region × Year	✓	✓	✓
Municipality Characteristics TT	✓	✓	✓
Individual Covariates	✓	✓	✓

The table shows the impact of the group average gold shock for ex-combatants located in municipalities with low and zero gold mine production. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.27 of supplementary material.

criminality. However, this approach has been criticized: it is vulnerable to measurement error due to projection by respondents of their own behavior and by limitations in the remembering or observing of the activities of peers, thus increasing the crucial correlation between own and peer criminality (Meldrum, Young and Weerman, 2009).

On the other hand, although I do not have a measure of crime different from the administrative information (that is, panel information for the entire sample of 16,000 ex-combatants), other studies, mainly Daly, Paler and Samii (2020), mention that around 7% of criminals are not reflected in the administrative information (based on a survey of close to 1,000 ex-combatants). In this study, the authors refer to administrative data as 'the most defensible way to operationalize illicit behavior.' Additionally, a reason for introducing fixed effects is that we hope to control for, in some way, people in different types of networks (e.g., large or small) who have different abilities to avoid being captured. In any case, it is possible that if we are missing stronger networks with members who are better at hiding, we are measuring a lower bound effect.

Additionally, following (VanderWeele and Li, 2019, p. 1825), for measurement error to fully explain the effect between the treatment and the error-prone outcome, the magnitude of the error, in this case calculated as the impact of the economic shock on "captures" not through "crime," must be at least as large as the observed association between the treatment and captures, which seems implausible. This situation would occur if, for example, the relationship between the economic shock and the arrests is due to systematic corruption of the police or ratting out by ex-combatants, neither of which has anything to do with criminal activities.

Finally, one may worry that captures reflect law enforcement capacity and the results reflect the contagion of 'law enforcement capacity' instead of contagion of crime. For the peer effect to result from an increase in police activity that is not related to contagion of criminal activity, there should be a reason why individuals who are committing crimes independently and live in different municipalities are more likely to be captured than other individuals committing crimes. If they have the same level of criminal activity, but that activity is independent from the activity of their peers, this should also be true for other ex-combatants who live in the same municipality (and not only those connected to other criminals). However, we don't observe this: ex-combatants living in municipalities not affected by the shock are more likely to be arrested 'only' when they are connected to other ex-combatants who participated in criminal activities. For example, when we consider the example in figure 4, we see an increase in the value of the outcome for $j's$ actions, not for l's, as a consequence of $i's$ or $k's$ actions.

H The Effect of the Economic Shock on Mobility

The following table present the relationship between the mean economic shock and mobility.

Table A 6: The Effect of the Economic Shock on Mobility

	Moved to gold municipality				
	(1)	(2)	(3)	(4)	(5)
Average Shock	0.0418***	0.0418***	0.0406***	0.0397***	0.0396***
	(0.0101)	(0.0101)	(0.0110)	(0.0116)	(0.0116)
Mean of Outcome	0.0050	0.0050	0.0049	0.0048	0.0048
S.D. of Outcome	0.0703	0.0703	0.0697	0.0694	0.0694
Observations	66,640	66,640	64,821	61,565	61,562
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

The table shows the effect of the mean of the gold shock of the group on the mobility of ex-combatants. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.28 of supplementary material.

I Dyad Analysis

I conduct a dyad analysis, in which instead of considering the group-to-individual ($g - i$) effect, I rearrange the data to estimate the individual-to-individual ($i - j$) effect. In particular, I use three sets of ex-combatant fixed effects that vary by year to restrict attention to the economic shock for individuals within the same education, socioeconomic stratum, and region groupings. Instead of looking at the effect of the average criminality of the network, this estimation focuses on the one-to-one relations, enabling me to include additional fixed effects. While the theoretical expectations refer to the group-level effect, these results are important because they clearly show the link between criminal activity among peers living in different municipalities while controlling for additional individual-level characteristics. In the dyad analysis, individuals i and j are connected if they belonged to the same subunit and had the same rank during the conflict. For reasons of robustness, I exclude dyads with individuals in the same municipality and include i-level fixed effects. In particular, I use three sets of ex-combatant fixed effects that vary by year to restrict attention to the economic shock for individuals within the same education, socioeconomic stratum, and region groupings. I estimate the following OLS regression:

$$Y_{it} = \beta \text{ Wartime peer economic shock}_{jt} + \mu_{ei} + \gamma_{si} + \delta_{ri} + \epsilon_{it}, \tag{8}$$

where *Wartime peer economic shock*$_{jt}$ is the economic change to i's connections and μ_{ei}, γ_{si}, and δ_{ri} are ex-combatant-level socioeconomic stratum, education, and region fixed effects, respectively.

Table A 7: Dyad Analysis: Estimates of Wartime Peers' Economic Shock on Ex-combatant's Criminality

	All Observations		Gold Production below sample mean		>100 Members in Group	
	Captures	Red-Handed	Captures	Red-Handed	Captures	Red-Handed
Wartime Economic Shock	0.0005***	0.0005***	−0.00003	0.0003***	0.002***	0.001***
	(0.0001)	(0.00005)	(0.0001)	(0.0001)	(0.0005)	(0.0004)
Observations	11,974,898	11,974,898	6,563,873	6,563,873	231,825	231,825
Ex-combatant level fixed effects:						
Education	✓	✓	✓	✓	✓	✓
Economic stratum	✓	✓	✓	✓	✓	✓
Region	✓	✓	✓	✓	✓	✓

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All specifications are estimated using OLS and include the fixed effects described in Equation 8.

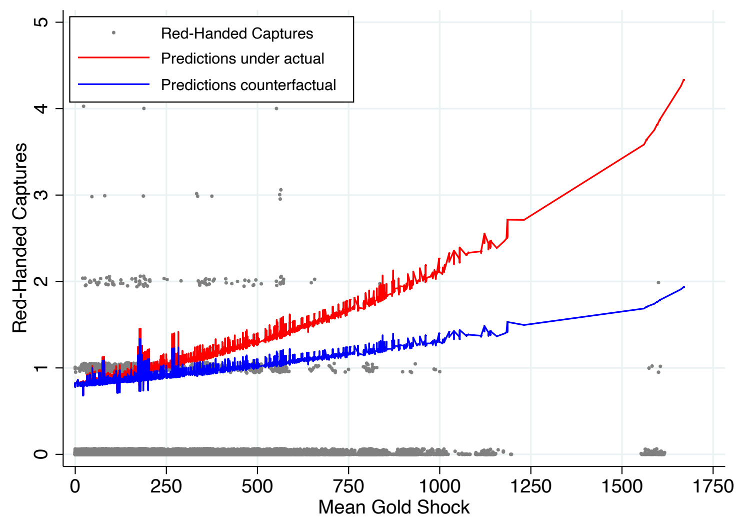
The results are presented in table A.6. Criminality increases with the economic change to wartime peers. The analysis includes several additional robustness checks: columns 1 and 2 show the effect of the economic shock for all observations, including red-handed and non-red-handed captures. Columns 3 and 4 show the results for individuals living in municipalities with levels of gold production that are less than the mean, and columns 5 and 6 show the results for groups of less than 100 members. The coefficients are significant, though considerably smaller than those of the main analysis. This is to be expected, given that the interpretation in the dyad analysis refers to the effect of a single pair, while the interpretation in the group-level analysis refers to the criminality of the entire wartime network.

Overall, the dyad analysis results are in line with the results of the group-level analysis. The substantial effects of peers' crimes that go through wartime ties thus suggest that the network of ex-combatants, arguably weaker after the conflict, could affect recidivism, particularly in the presence of illegal markets.

J Counterfactual Experiment

I perform a counterfactual analysis below in which I look at the predicted values of captures estimated in the main analysis, following Equation 6, when we reduce the peer effect to different values. Specifically, I look at the effect of (1) a gold-price shock under the actual conditions and (2) a gold-price shock with wartime connections randomly reduced by half.

Figure A 8: Predicted Values of Red-handed Captures under Actual and Counterfactual Conditions



[h]

Figure A.8 shows the difference in the predicted values of Equation 6 when we reduce β, the peer effect, by 50%. Model results in Table A.44 of supplementary material. The blue line represents the predicted values of captures derived from the main specification. The red line represents counterfactual predictions, that is, the predicted values when we look at the difference between the predictions in Equation 6 and the predictions when we set β to 50%. The difference between the two lines measures the difference that an intervention reducing β by 50% would have on capture rates. Red-handed captures decrease around 12% when we reduce the effect of the peer effect by 50%. This is a notable implication of the present study: the reduction in crime is due to the reduction of peer effects, even when the economic factors are the same under both conditions.

What other strategies exist to reduce criminal connections? Two types of initiatives are promising, the first being economic-oriented activities such as productive projects in which community members and outsiders (ex-combatants) participate together. Such initiatives have recently been implemented for integrating immigrants in Uganda, where the projects involve refugees and community members (examples of such development activities are discussed in Grossman and Zhou (2021)). The Colombian Agency of Reincorporation has in fact implemented similar initiatives. A detailed evaluation of these initiatives is a promising avenue of research. Such studies may complement the evidence on the positive effect of giving money and psychological assistance to vulnerable populations. In this way, the initiatives promoted by the government imply the joint participation of community members that expand the non-criminal networks of ex-combatants (while not negatively affecting other positive networks such as those offering emotional support). Other social-oriented activities refer to initiatives implemented during the reintegration process in which ex-combatants and community members work together to reduce prejudice (Ugarriza and Nussio, 2017). Another way to help ex-combatants change their network structure is to locate some of the transition sites usually used in peace processes in places far from the main operation centers during the conflict. This enables people, at least for a time, to depend more on the receiving community than on the networks they had during the war.

K Survey on the Social Connections of Former Combatants

In this section I provide additional information about the social connections of former combatants based on an original survey of members of armed organizations in Colombia. I expand on the relevance of social connections of former combatants by showing what connections were more important during the conflict and by explaining what factors are related to criminality.

K.1 Sample

I use administrative data from an original survey along with data from the Colombian Agency of Reintegration and police records. The survey was conducted by various regional teams coordinated by the Universidad Externado de Colombia between July and September of 2019, resulting in a sample of 448 ex-combatants who were contacted by the ACR in municipalities with over 100 ex-combatants registered with the agency. The final sample contains ex-combatants living in 26 different municipalities. It includes 163 self-identified former members of the paramilitary group AUC, 125 former members of the guerrilla group FARC, 37 former members of the guerrilla group ELN, and 9 individuals from other illegal armed groups.[1]

Even with several threats of sampling bias, the sampling procedures still permit the construction of a relatively representative sample compared to other samples of hard-to-reach populations. I compare the aggregate data of the sample with aggregate data of the complete population of ex-combatants in the reintegration program. The sample has a significantly larger amount of former combatants of the FARC in several municipalities, but other covariates are very similar.

During the survey, enumerators started with an informal conversation about connections during the conflict, then asked questions about basic demographics, survey questions about wartime, and some questions about perceptions of crime and reintegration.

K.1.1 Ethical Considerations

This survey adheres to the APSA's Principles and Guidance on Human Subject Research. The survey was reviewed and approved by the New York University IRB under certificate number IRB-FY2018-2047. The survey was also approved by the ARN Office of the Colombian Government.

[1] The group of origin, as many other variables, came directly from the ACR and I currently don't have all the administrative information on all of the respondents.

Participation in the research was completely voluntary. Before subjects participated in the survey, a local facilitator read a consent statement to them in Spanish. We asked subjects to give their consent verbally. We used a standard consent form recommended by the IRB at New York University.

No deception was involved in this study.

We did not anticipate any risks of harm beyond those encountered in everyday life and indeed none occurred.

At no point were subjects' names asked. Enumerators identified subjects only with a random code.

The ethics board at NYU approved the study. The ARN, from the Colombian Government, also approved the study. Other country experts also stated that the study complied with norms and laws in Colombia.

Participants were not pay to participate in the activity.

Participant pool was diverse: participants came from different municipalities of the country where a local ARN office was present.

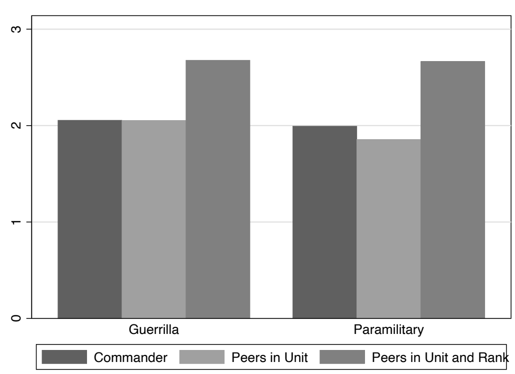
None of the groups were vulnerable or marginalized. The ex-combatants in the study were all participants in the legal ex-combatant reintegration program.

K.2 Ex-combatants' Social Connections

The survey contains questions about the intensity of the interaction with other combatants during and after the conflict. Figure A.9 shows the extent to which individuals shared their time with members of their same subunit and rank, members of the same subunit but not the same rank and commanders of their unit, both before and after the conflict. Based on the conversations and the survey, combatants spent more time with members of their same unit and their same rank, than with commanders or members of other positions. This is true for the members of all armed groups.

More than 70% of respondents said they spent a lot of time with members of the same unit and same rank during the conflict. This finding provides some support for the selection of this type of link, given that it is the most extensive connection for ex-combatants.

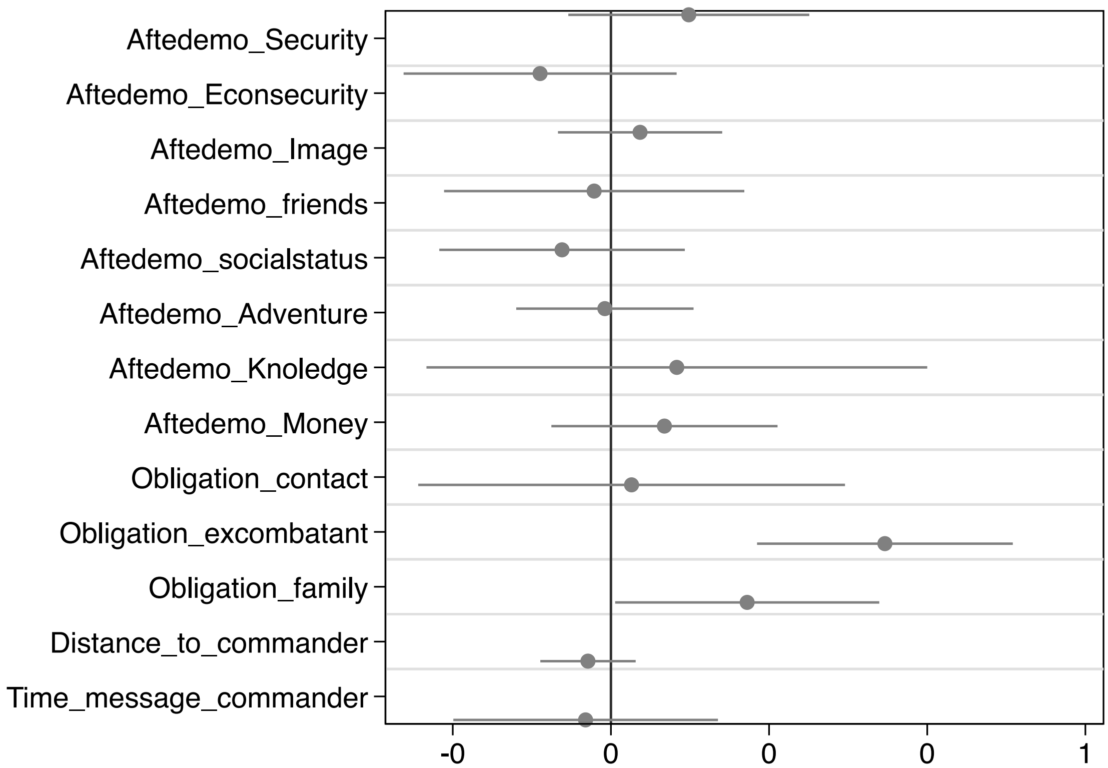
Figure A 9: Connections during the Conflict



Note: Time spent with other combatants in a 0 ("Never") to 4 ("A lot") scale.

Finally, to complement the conjecture that connections to former peers are relevant only for a specific set of ex-combatants, I regress a set of variables related to perception of the post-conflict period (after demobilization feelings of security and economic conditions; feeling of obligation towards family and former combatant) and a measure of crime acceptance based on the answers to a list experiment (to avoid directly asking about crime acceptance). The results, presented in Figure A.10, are for the paramilitary-only sample. We see a positive and significant relationship in the coefficient of 'feeling obligations toward and being an ex-combatant.'

Figure A 10: Crime Acceptance during Post-conflict



Note: Each coefficient is the result of a regression of the crime acceptance on the corresponding variable, including location and enumerator fixed effects with robust standard errors. Complete model results in Table A.45 of supplementary material.

Additional Online Appendix for "Peer Effects and Recidivism: Wartime Connections and Criminality among Colombian Ex-combatants"

by Mateo Vásquez-Cortés

A Main Effect Clustered at the Individual Level

As a robustness check, in table A.7 I replicate the analysis, but cluster standard errors at the individual rather than the group level to account for the fact that connections in the same municipality may experience similar economic changes. The estimations are equivalent to the main results for red-handed and non-red-handed captures, with and without the additional tests in the main results.

Table A 8: Main Effect Clustered at Individual Level

	Red-handed Captures				
	(1)	(2)	(3)	(4)	(5)
Panel A: Economic shock and average shock for the group					
Economic Shock	0.393***	0.394***	0.372***	0.379***	0.380***
	(0.113)	(0.113)	(0.115)	(0.118)	(0.118)
Average Shock	0.256**	0.256**	0.275**	0.289**	0.286**
	(0.116)	(0.116)	(0.119)	(0.123)	(0.123)
Panel B: Criminal peer effects					
Peer Effect	0.394***	0.394***	0.425***	0.433***	0.430***
	(0.151)	(0.151)	(0.154)	(0.156)	(0.156)
Mean of Outcome	0.0242	0.0242	0.0244	0.0243	0.0244
S.D. of Outcome	0.1697	0.1697	0.1703	0.1704	0.1704
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

The dependent variable include red-handed arrests for the 2013—2016 period. Panel A shows the result of estimating Equation 6, where the first row represent the effect of the shock for individual i and the second row represents the average shock for the group g. Panel B shows the estimation explained in Equation 5. Standard errors in parentheses clustered at the individual level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.29 of supplementary material.

B Peacetime Networks, Positive Economic Changes, and Non-criminal Activities

Here I show that changes in the price of gold are not associated with variation in captures for a placebo network of ex-combatants. For the test, I define two peaceful post-conflict networks: the first placebo network defines members on the basis of being affiliated with the same territorial entity of the Colombian Agency of Reincorporation (ARN). That is, two ex-combatants belong to the same network if they are registered with the same agency office. To complement the test, I create another placebo group in which people must be registered not only with the same local office but also live in the same region.

Both tests aim to show that belonging to a wartime network is crucial to explaining the results beyond the connection or other municipal characteristics. The point is that it is unlikely that gold mining affects economic opportunities for people who don't have anything to do with the business or are connected to an affected wartime peer. Results shown in table A.9 support these claims.

Table A 9: Test with Non-criminal Activities

	Number of Actions ARN (1)	Number of New Returns (3)
Economic Shock	0.475	0.216*
	(0.330)	(0.110)
Average Shock	0.340	-0.0214
	(0.251)	(0.110)
Peer Effect	0.417	-0.110
	(0.273)	(0.602)
Mean of Outcome	1.2459	0.2345
S.D. of Outcome	1.4820	0.4929
Observations	46,542	34,906
Municipality, Year, and Group FE	✓	✓
Additional Controls	✓	✓

This table presents results on the impact of a gold-price shock on non-criminal actions. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.30 of supplementary material.

Another placebo test refers to the participation in non-criminal activities such as returns to the agency and the number of interactions with the agency (Acciones con la ARN). In both cases (table A.18), we also have a panel database that enables us to perform the test. Again, we find that gold price changes do not differentially affect people's participation in these activities.

Finally, we show that there is no effect on crime levels due to changes in the price of a legal commodity such as oil for the same period (table A.10, and also we do not see an effect when we interact local-level production with the price of the following year, reducing selection concerns (table A.11).

Table A 10: Test with Different Post-conflict Networks

	(1)	(2)
	Red-Handed Captures	
	Peacetime group 1: (National Reintegration Office peacetime network)	
Economic Shock	0.178	0.134
	(0.124)	(0.110)
Average Shock	-0.00138	0.00765
	(0.139)	(0.129)
Peer Effect	-0.00782	0.0542
	(0.793)	(0.879)
	Peacetime group 2: (National Reintegration Office and region peacetime network)	
Economic Shock	0.155	0.133
	(0.121)	(0.117)
Average Shock	0.0123	0.0169
	(0.156)	(0.151)
Peer Effect	0.0734	0.113
	(0.892)	(0.951)
Municipality, Year, and Group FE	✓	✓
Time Trends		✓
Region × Year		✓
Municipality Characteristics TT		✓
Individual Covariates		✓

This table presents results on the impact of the economic shock through non-wartime networks. Standard errors in parentheses clustered at the group and peacetime levels, respectively in top and lower panels. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender, and race. *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Tables A.31 and A.32 of supplementary material.

Table A 11: Placebo Test: Oil Shock and Criminality

	(1) *Red-handed Captures*	(2) *Captures*
Oil Shock	-0.00498	-0.00371
	(0.0139)	(0.0162)
Average Oil Shock	0.000658	0.0103
	(0.00979)	(0.0139)
Peer Effect	-0.152	1.562
	(2.312)	(3.368)
Mean of Outcome	0.0239	0.0371
S.D. of Outcome	0.1711	0.2105
Observations	48,308	48,308
Municipality, Year, and Group FE	✓	✓

This table presents the results on the impact of economic oil shock on criminality and peer effects. Standard errors in parentheses clustered at the group-peacetime level. Results follow the estimation of the main results explained in the main text. Oil shock is the interaction of kms of pipelines before the study period with the international price of gold. None of the results are significant.

Table A 12: Placebo Leads of Treatment

	(1) *R-H Captures*	(2) *R-H Captures*	(3) *Captures*	(4) *Captures*
Economic Shock	0.00554	0.00564	0.00733	0.00611
	(0.00546)	(0.00548)	(0.00560)	(0.00536)
Average Group Shock	0.195*	0.149	0.148	0.0506
	(0.109)	(0.129)	(0.126)	(0.142)
Mean of Outcome	0.0269	0.0271	0.0390	0.0391
S.D. . of Outcome	0.1799	0.1808	0.2140	0.2146
Observations	24,388	23,110	24,388	23,110
Municipality, Year, and Group FE	✓	✓	✓	✓
Time Trends		✓		✓
Region × Year		✓		✓
Municipality Characteristics TT		✓		✓
Individual Covariates		✓		✓

Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.33 of supplementary material.

C Spatial Correlation Test

There exists the possibility that the way in which the economic shock variable is constructed may cause the variable to exhibit a spatial correlation that may confound the peer effect. To reduce this concern, I use Conley's correlation estimation method to account for spatial correlation in the data. Table A.13 shows the results.

Table A 13: Main Results with Auto-correlation Tests

	Red-Handed Captures			
	50 kms	100 kms	150 kms	200 kms
	(1)	(2)	(3)	(4)
Economic Shock	0.385**	0.385**	0.385**	0.385**
	(0.173)	(0.177)	(0.179)	(0.175)
Average Group Shock	0.227**	0.227**	0.227**	0.227**
	(0.102)	(0.100)	(0.0951)	(0.101)
Peer Effect	0.374**	0.374*	0.374**	0.374*
	(0.187)	(0.192)	(0.187)	(0.197)
Mean of Outcome	0.0239	0.0239	0.0239	0.0239
S.D. of Outcome	0.1711	0.1711	0.1711	0.1711
Observations	36,366	36,366	36,366	36,366
Municipality, Year, and Group FE	✓	✓	✓	✓
Time Trends	✓	✓	✓	✓
Individual Covariates	✓	✓	✓	✓

Standard errors in parentheses clustered using auto-correlational analysis. Individual controls include age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.34 of supplementary material.

I implement the method, assuming spatial dependence between observations within 50, 100, 150, and 200 km. Although the standard errors are bigger, the results remain similar in magnitude and all are statistically significant.

D Types of Captures: Collective Crimes and Economic Crimes

The division of crimes into collective and individual crimes must be done with care. Especially when we are talking about crimes like drug possession or weapons possession, the collective nature of the crimes may not be obvious.

Table A 14: Crime Classification

Crime	Type	Participation	Gang Flag
Drug trafficking, possession and distribution*	Drug	Collective	Yes[2]
Organized Crime/Conspiracy*	Violent	Collective	Yes
Illegal arms possession and trafficking or production*	Violent	Collective	Yes
Homicide	Violent	Collective	Yes
Theft*	Property	Collective	Yes
Attack or assault	Violent	Collective	No
Extortion*	Violent	Collective	Yes
Illegal possession and trafficking of military arms and ammunition*	Violent	Collective	Yes
Domestic violence	Violent	Individual	No
Threat/Intimidation	Violent	Collective	Yes
Illegal use of resources	Property	Collective	Yes
Use of false identification	Property	Individual	No
Terrorism	Violent	Collective	Yes
Kidnapping*	Violent	Collective	Yes
Sexual harassment	Violent	Individual	No
Fraud*	Property	Collective	No
Rebellion	Violent	Collective	Yes
Attack against authority	Violent	Collective	Yes
Forced disappearance	Violent	Collective	Yes
Household food assistance*	Property	Individual	No
Property assault*	Property	Collective	Yes
Animal abuse	Violent	Individual	No
Negligent injuries car accident	Property	Individual	No

This table presents a list of group of crimes and their type, with participation specified as either individual or collective, and point out the crimes that have a high probability of being flagged by the police for a known gang affiliation at the moment of capture based on (Khanna et al., 2023). An * indicates a crime listed in the appendix table that are related to economic opportunities.

First, it is worth noting that the division comes from the Colombian national police following the study of Khanna et al. (2023). In that case, however, it is easier to separate drug possession from drug trafficking, for example. In our case, the police information was already added for those captures. We present the division based on the data we have.

The classification of participation as collective is based on the following: even though people can carry out these activities as individuals (for example, using drugs or having a gun), this implies knowing someone in the illegal market who enables one to access drugs or weapons. Neither activity was legal in Colombia during the period of study.

In Warr (2002), collective crimes also refer to those that cannot be achieved without the participation of others. Although our classification follows this premise, it is worth noting that it is not perfect in all cases.

In particular, it is not always the case that crimes such as arms possession and homicide are collective undertakings. For that reason, to complement the analysis with collective crimes, I remove homicides and weapons possession from the 'collective crimes results' in table A.17, and the results remain unchanged in magnitude and significance.

Table A 15: Economic Shock and Peer Effects for Collective Crimes Only — All captures

	All Captures — Collective Crimes				
	(1)	(2)	(3)	(4)	(5)
Panel A: Economic shock and average shock for the group					
Economic Shock	0.370***	0.370***	0.290***	0.238**	0.239**
	(0.103)	(0.103)	(0.0986)	(0.110)	(0.110)
Average Shock	0.100	0.100	0.117	0.149	0.147
	(0.106)	(0.106)	(0.103)	(0.109)	(0.109)
Panel B: Criminal peer effects					
Peer Effect	0.214	0.214	0.287	0.386	0.380
	(0.207)	(0.207)	(0.221)	(0.247)	(0.248)
Mean of Outcome	0.0281	0.0281	0.0280	0.0281	0.0281
S.D. of Outcome	0.1827	0.1827	0.1827	0.1830	0.1830
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

The dependent variable include all ex-combatant collective crimes for the 2013—2016 period. Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. The economic shock is defined as the interaction of the natural logarithm of the international price of gold and illegal gold production. Panel B shows the estimation in Equation 5, representing the effect of wartime peers' arrests on $i's$ criminality. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female) and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.35 of supplementary material.

Finally, it is worth mentioning other types of capture characteristics that may be relevant to this article's main argument. Some crimes, such as robbery, extortion, and drug trafficking, may be related to economic opportunities, while other types of crimes, such as sexual harassment and personal attacks, are not. According to this classification, the estimated peer effects come primarily from criminal activities related to economic opportunities.

The division between economic and non-economic crimes is an important one. Therefore, I propose a division of crimes by their economic or non-economic nature. This classification is arbitrary: it is not obvious how to categorize some captures as economic or non economic based on the classification of teh National Police. Table A.14 provides the list of captures used in the analysis. The analysis is presented in table A.18. I find a significant peer effect for offenses classified as economic, but we do not find a definitive result for non-economic crimes.

Table A 16: Economic Shock and Individual Crimes

	Red-handed Captures — Individual Crimes				
Economic Shock	0.00907	0.00916	0.00433	0.0214	0.0215
	(0.0217)	(0.0217)	(0.0256)	(0.0303)	(0.0303)
Average Shock	0.0443*	0.0444*	0.0425	0.0342	0.0342
	(0.0257)	(0.0258)	(0.0262)	(0.0280)	(0.0280)
Mean of Outcome	0.0010	0.0010	0.0010	0.0010	0.0010
S.D. of Outcome	0.0321	0.0321	0.0323	0.0321	0.0321
Observations	36,746	36,746	36,340	34,868	34,865
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

The dependent variable include red-handed captures for individual crimes for the 2013—2016 period. Panel A shows the result of estimating Equation 6, where the first row represents the effect of the shock for individual i and the second row represents the average shock for the group g. The economic shock is defined as the interaction of the natural logarithm of the international price of gold and illegal gold production. Panel B shows the estimation in Equation 5, representing the effect of wartime peers' arrests on $i's$ criminality. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include: age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level. Complete model results in Table A.36 of supplementary material.

Table A 17: Collective Crimes (Without Homicides and Arms Possession)

	(1) *Red-handed captures* (Collective Crimes)
Economic Shock	0.261***
	(0.0773)
Average Shock	0.236**
	(0.0918)
Peer Effect	0.475***
	(0.141)
Mean of Outcome	0.0146
S.D. of Outcome	0.1368
Observations	34,865
Municipality, Year, and Group FE	✓
Time Trends	✓
Region × Year	✓
Municipality Characteristics TT	✓
Individual Covariates	✓

The dependent variable include only red-handed captures for collective crimes in the 2013—2016 period excluding homicide and arms possession. Table presents the main results of collective crimes in the document. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.37 of supplementary material.

Table A 18: Results for Economic and Non-economic Crimes

	(1) Economic Crimes	(2) Non-economic Crimes
Economic Shock	1.304	0.0354
	(1.189)	(0.0450)
Average Shock	3.168**	0.0448
	(1.501)	(0.0437)
Peer Effect	0.708***	0.559
	(0.228)	(0.492)
Mean of Outcome	0.2717	0.0038
S.D. of Outcome	0.5255	0.0637
Observations	1,844	34,865
Municipality, Year, and Group FE	✓	✓
Time Trends	✓	✓
Region × Year	✓	✓
Municipality Characteristics TT	✓	✓
Individual Covariates	✓	✓

The dependent variable include only red-handed captures for economic vs. non-economic crimes in the 2013–2016 period excluding homicide and arms possession. The table presents the main results for red-handed captures in this article. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level, and * is significant at the 10% level. Complete model results in Table A.38 of supplementary material.

E Additional Mobility Controls

In this section I include specifications with three additional variables directly related to the labor market: distance from the municipality to the largest local market, number of persons who moved to that municipality between the 1990s and early 2000s, and a measure of mean historic wages in the municipality. These variables control for potential biases coming from differential trends in municipalities that are connected to more-historic labor migration.

Table A 19: Main Results with Mobility Controls

	(1) Historic mobility	(2) Ln Wages	(3) Mobility & wages
		Red-Handed Captures	
Economic Shock	0.471***	0.383***	0.0940
	(0.109)	(0.102)	(0.213)
Average Group Shock	0.233	0.356***	0.272*
	(0.157)	(0.127)	(0.163)
Peer Effect	0.330*	0.482***	0.743
	(0.181)	(0.130)	(0.476)
Mean of Outcome	0.0271	0.0258	0.0273
S.D. of Outcome	0.1810	0.1765	0.1815
Observations	19,386	29,311	18,427
Municipality, Year, and Group FE	✓	✓	✓
Time Trends	✓	✓	✓
Region × Year	✓	✓	✓
Municipality Characteristics TT	✓	✓	✓
Individual Covariates	✓	✓	✓

The table presents main results including controls for labor mobility. Standard errors in parentheses clustered using auto-correlational analysis. Municipality characteristics include pre-treatment levels of share of historic population from outside the municipality and pre-treatment measures of wages. Individual controls include: age, gender (female), and race (indigenous and afro). *** is significant at the 1% level, ** is significant at the 5% level and, * is significant at the 10% level. Complete model results in Table A.39 of supplementary material.

F Descriptive Analysis: Post-conflict Criminality

This section presents some descriptive analyses of ex-combatant criminality in Colombia. The focus is exclusively on paramilitaries and shows the relationship between demographic characteristics of ex-combatants and confidential crime data between 2013 and 2016.

The first part describes the characteristics of those arrested during the study period and their relationship with social networks and criminal opportunities at the municipal level.

Table A 20: Pooled Descriptive Relationships

	Dependent variable:			
	Captures		Red-handed Captures	
	(1)	(2)	(3)	(4)
Illegal Gold Mines	0.067***		0.051***	
	(0.016)		(0.012)	
Mean Gold Price		0.013***		0.008***
		(0.001)		(0.001)
Observations	1,239	2,343	1,239	2,343
R^2	0.013	0.030	0.015	0.026

Note: *** is significant at the 1% level, ** is significant at the 5% level and, * is significant at the 10% level. Complete model results in Table A.40 of supplementary material.

Figure A 11: Crime and Reintegration Index

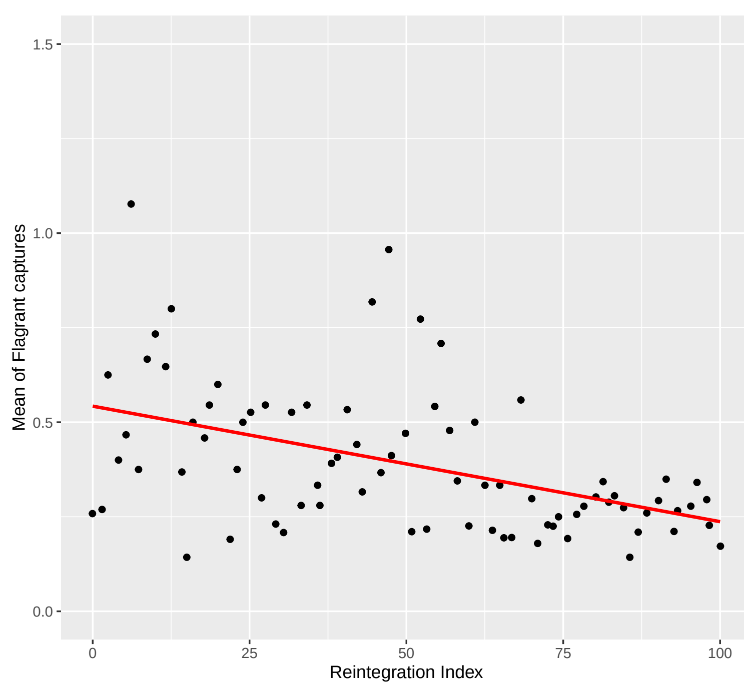


Figure A 12: Crime and Education

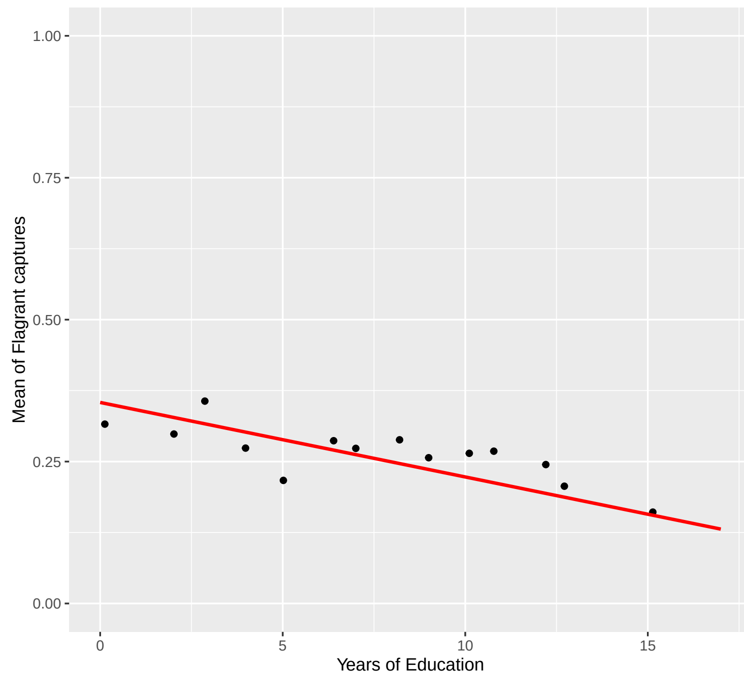


Figure A.12 shows the relationship between the average number of flagrant (red-handed) captures and the reintegration index assigned by the Colombian reintegration agency. In both cases, we observe the expected relationship regarding the level of recidivism, years of education, and the index measure used by the reintegration agency to measure the reintegration of ex-combatants.

The second part focuses on the descriptive relationship between changes in returns to illegal activities related to illegal mining at the municipal level and the criminality of ex-combatants. In addition, I study other social network factors central to the literature on social networks and crime.

Finally, tables A.20 and A.21 describe the relationship between the number of illegal gold mines, the price of gold, and a measure of centrality (degree centrality or the size of the group) with the crime outcomes used in this paper (captures and red-handed captures). The results pool the panel's data and show a positive and significant relationship between these variables and the number of captures. Both results are in line with what is argued in this paper about the relationship between gold mining and ex-combatant crime.

The second results confirm other findings of the broader literature on social networks and criminality, even if my analysis here is narrower and only refers to a measure of centrality (degree centrality). In this case, it is worth exploring other alternative measures of centrality and their relationship with criminal behavior.

Table A 21: Degree Centrality and Criminality

	Red-handed Captures				*Total Captures*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree Centrality	0.0253***	0.0212***	2.684***	3.270***	0.0186***	0.0152**	3.900***	4.407***
	(0.00536)	(0.00567)	(0.248)	(0.258)	(0.00636)	(0.00672)	(0.292)	(0.304)
Mean of Outcome	0.2165	0.2164	0.2164	0.2164	0.3260	0.3260	0.3260	0.3260
S.D. of Outcome	0.6388	0.6380	0.6381	0.6381	0.7856	0.7850	0.7851	0.7851
Observations	66,977	66,927	66,912	66,909	66,977	66,927	66,912	66,909
Municipality FE		✓	✓	✓		✓	✓	✓
Wartime FE			✓	✓			✓	✓
Individual Covariates				✓				✓

This table presents OLS estimation of a measure of degree centrality and cumulative number of captures, both red-handed (columns 1–4) and total (columns 5–8). Columns 2 and 4 add municipality fixed effects and columns 3 and 7 include wartime network fixed effects. Individual controls include age, gender (female), and race (indigenous and afro). The period includes all captures recorded by the National Police of Colombia.
*** is significant at the 1% level, ** is significant at the 5% level and, * is significant at the 10% level.
Complete model results in Table A.40 of supplementary material.

G Historic Gold Production

If there are economic opportunities in an activity like gold mining, even if it is legal, one might expect the results to be similar. Most of the mining activity in Colombia is illegal. The gold mining data are based on places where there are potential gold mines identified by the government (only 70 out of more than 600 municipalities have a mines with legal titles).

It is still worth studying whether we can find a similar effect in places where historically more gold is produced. For this reason, I perform an analysis using gold production in 2004 (based on data from Dube and Vargas (2013)). The results are presented in table A.22 . Although there is a positive relationship between the change in price and ex-combatant captures, it is around 15 times smaller and not significant. I also do not find a significant relationship in terms of peer effects. Nevertheless, the analysis using legal gold mines can shed some light on the relevance of illegal mines to my argument: only for illegal mines, and not for places with historical production, do we find an effect of gold price changes on crime.

Table A 22: Economic Shock and Peer Effects for Red-handed captures — Historic Gold Production

	Red-handed Captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.0154	0.0151	0.0298	0.0434	0.0407
	(0.0756)	(0.0756)	(0.0802)	(0.105)	(0.105)
Average Shock	0.0804	0.0804	0.0787	0.100	0.102
	(0.0869)	(0.0868)	(0.0926)	(0.103)	(0.103)
Peer Effect	0.839	0.842	0.725	0.698	0.714
	(0.711)	(0.715)	(0.617)	(0.522)	(0.534)
Mean of Outcome	0.0202	0.0202	0.0200	0.0202	0.0202
S.D. of Outcome	0.1541	0.1541	0.1537	0.1544	0.1544
Observations	26,328	26,328	26,044	23,663	23,663
Municipality, Year, and Group FE	✓	✓	✓	✓	✓
Time Trends		✓	✓	✓	✓
Region × Year			✓	✓	✓
Municipality Characteristics TT				✓	✓
Individual Covariates					✓

This table results from a replication of the main analysis but uses an historic measure of gold production at the municipality level that does not distinguish between legal and illegal production. Standard errors in parentheses clustered at the group-wartime level. Municipality characteristics include pre-treatment levels of poverty, population, distance to Bogotá, and kms of paved roads. Individual controls include age, gender (female), and race (indigenous and afro). Complete model results in Table A.41 of supplementary material.

H Full Model Results of Main Document

For presentation purposes, the results in the main text (Tables 1 and 2) and Supplemental Materials (Tables A.2, A.4, A.5, A.6, A.7, A.8, A.9, A.10, A.12, A.13, A.15, A.16, A.17, A.18, A.19, A.21, and A.22) do not present estimates for coefficients on the control variables. These full results are presented here.

Table A 23: Economic Shock and Peer Effects for fragrant captures - Full Model Results Table 1

	Red-handed captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.393***	0.394***	0.372***	0.379***	0.380***
	(0.0881)	(0.0882)	(0.0885)	(0.0932)	(0.0932)
Average Shock	0.256**	0.256**	0.275**	0.289**	0.286**
	(0.104)	(0.104)	(0.107)	(0.114)	(0.114)
time t		0.00373	0.00382	0.00556	0.00519
		(0.0206)	(0.0208)	(0.0209)	(0.0207)
region 2 x time t			-0.00105	-0.00326	-0.00329
			(0.00227)	(0.00527)	(0.00528)
region 3 x time t			0.00177	0.000872	0.000756
			(0.00488)	(0.00499)	(0.00500)
region 4 x time t			0.000209	-0.000431	-0.000356
			(0.00315)	(0.00411)	(0.00413)
region 5 x time t			-0.00790	-0.0155**	-0.0155**
			(0.00519)	(0.00697)	(0.00691)
poverty x time t				0.000902	0.000913
				(0.00923)	(0.00928)
population x time t				-1.38e-09*	-1.38e-09*
				(8.06e-10)	(8.09e-10)
distance Bogota x time t				0.000000825	0.000000854
				(0.0000113)	(0.0000113)
paved roads x time t				0.00000890	0.00000978
				(0.0000205)	(0.0000206)
age					-0.000762***
					(0.000145)
female					-0.0188***
					(0.00216)
black					-0.00359
					(0.00404)
indigenous					0.00420
					(0.00882)
Constant	0.0634***	0.0522	0.0546	0.0467	0.0783
	(0.0144)	(0.0620)	(0.0620)	(0.0641)	(0.0624)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 24: Economic Shock and Peer Effects - Collective Crimes Only - Full Model results Table 2

	Red-handed captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.343***	0.344***	0.315***	0.279***	0.279***
	(0.0777)	(0.0777)	(0.0740)	(0.0776)	(0.0776)
Average Shock	0.167*	0.168*	0.188**	0.210**	0.208**
	(0.0867)	(0.0869)	(0.0894)	(0.0974)	(0.0971)
time t		0.0206***	0.0210***	0.0198***	0.0194***
		(0.00414)	(0.00419)	(0.00623)	(0.00644)
region 2 x time t			-0.00196	-0.00542	-0.00544
			(0.00193)	(0.00442)	(0.00444)
region 3 x time t			0.00360	0.00286	0.00278
			(0.00423)	(0.00430)	(0.00430)
region 4 x time t			-0.00162	0.00103	0.00107
			(0.00263)	(0.00335)	(0.00336)
region 5 x time t			-0.00544	-0.00877	-0.00873
			(0.00475)	(0.00616)	(0.00607)
poverty x time t				-0.00308	-0.00308
				(0.00763)	(0.00765)
population x time t				-4.03e-10	-4.02e-10
				(6.35e-10)	(6.36e-10)
distance Bogota x time t				0.00000808	0.00000810
				(0.00000925)	(0.00000927)
paved roads x time t				0.0000194	0.0000201
				(0.0000175)	(0.0000176)
age					-0.000571***
					(0.000120)
female					-0.0142***
					(0.00219)
black					-0.00646**
					(0.00298)
indigenous					0.00496
					(0.00792)
Constant	0.0436***	-0.0181	-0.0152	-0.0178	0.00659
	(0.0120)	(0.0162)	(0.0169)	(0.0175)	(0.0187)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 25: Economic Shock and Peer Effects - All Captures - Full Model Results Table A.2

	Red-handed captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.398***	0.398***	0.327***	0.319**	0.320**
	(0.121)	(0.121)	(0.120)	(0.128)	(0.128)
Average Shock	0.209*	0.209*	0.225**	0.251**	0.247**
	(0.113)	(0.113)	(0.110)	(0.115)	(0.115)
time t		-0.00433	-0.00384	0.0125	0.0122
		(0.0289)	(0.0290)	(0.0218)	(0.0217)
region 2 x time t			-0.00330	-0.00459	-0.00464
			(0.00258)	(0.00554)	(0.00556)
region 3 x time t			-0.00467	-0.00517	-0.00535
			(0.00694)	(0.00699)	(0.00698)
region 4 x time t			0.00360	0.000601	0.000730
			(0.00432)	(0.00572)	(0.00575)
region 5 x time t			-0.00560	-0.0114	-0.0113
			(0.0149)	(0.0203)	(0.0201)
poverty x time t				0.0117	0.0117
				(0.0137)	(0.0138)
population x time t				-1.09e-09	-1.08e-09
				(1.13e-09)	(1.14e-09)
distance Bogota x time t				-0.00000247	-0.00000238
				(0.0000124)	(0.0000124)
paved roads x time t				0.0000334	0.0000345
				(0.0000287)	(0.0000289)
age					-0.00102***
					(0.000171)
female					-0.0269***
					(0.00322)
black					-0.000502
					(0.00461)
indigenous					0.00890
					(0.0111)
Constant	0.0693***	0.0823	0.0851	0.0212	0.0625
	(0.0154)	(0.0879)	(0.0879)	(0.0667)	(0.0659)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 26: Analysis Excluding Larger Groups - Full Model results

	Red-handed Captures			
	(1)	(2)	(3)	(3)
	> 1,000 Members	> 500 Members	> 250 Members	> 100 Members
Peer Effect	0.409**	0.543**	0.820**	1.038*
	(0.159)	(0.271)	(0.359)	(0.540)
Economic Shock	0.379***	0.244	0.0897	-0.0159
	(0.108)	(0.169)	(0.198)	(0.221)
Average Shock	0.262**	0.290*	0.410**	0.432*
	(0.129)	(0.163)	(0.193)	(0.235)
age	-0.000682***	-0.000662***	-0.000638***	-0.000520***
	(0.000128)	(0.000135)	(0.000164)	(0.000189)
female	-0.0186***	-0.0196***	-0.0207***	-0.0186***
	(0.00230)	(0.00276)	(0.00302)	(0.00334)
black	-0.00316	-0.00525	-0.00260	0.000725
	(0.00424)	(0.00573)	(0.00688)	(0.0107)
indigenous	0.00570	0.00590	-0.00365	-0.000870
	(0.00911)	(0.0105)	(0.00889)	(0.0113)
time t	0.00705	0.0200**	0.0190	0.000733
	(0.0208)	(0.00907)	(0.0133)	(0.0183)
region 2 x time t	-0.00220	-0.00841	-0.00704	-0.00854
	(0.00546)	(0.00774)	(0.00831)	(0.00749)
region 3 x time t	0.00209	-0.00131	-0.00177	-0.000572
	(0.00506)	(0.00590)	(0.00655)	(0.00890)
region 4 x time t	-0.000862	0.00128	-0.00248	-0.000290
	(0.00418)	(0.00545)	(0.00784)	(0.00883)
region 5 x time t	-0.0160**	-0.0188**	-0.0192**	-0.00662
	(0.00707)	(0.00759)	(0.00790)	(0.00539)
poverty x time t	-0.000272	0.00362	0.0184	0.0185
	(0.00980)	(0.0139)	(0.0144)	(0.0177)
population x time t	-1.69e-09**	-1.68e-09*	-4.61e-10	4.10e-10
	(7.70e-10)	(9.67e-10)	(1.10e-09)	(1.31e-09)
distance Bogota x time t	-0.00000110	0.00000800	0.00000539	0.0000190
	(0.0000116)	(0.0000157)	(0.0000186)	(0.0000166)
paved roads x time t	0.00000517	0.00000641	0.0000209	-0.00000671
	(0.0000214)	(0.0000311)	(0.0000387)	(0.0000416)
Constant	0.107	0.0802*	0.0790	0.141*
	(0.0657)	(0.0414)	(0.0562)	(0.0832)
Municipality, Year, and Group FE	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 27: The effect of the economic shock for different levels of gold production - Full model Results

	Production below Mean (1)	Production below 25 Percentile (2)	No Gold Production (3)
		Red-Handed Captures	
Average Shock	0.339***	0.255**	0.303
	(0.104)	(0.109)	(0.291)
age	-0.000722***	-0.000807***	-0.000206
	(0.000151)	(0.000161)	(0.000282)
female	-0.0169***	-0.0175***	-0.0188***
	(0.00271)	(0.00316)	(0.00474)
black	-0.00394	-0.00577*	-0.0106*
	(0.00407)	(0.00349)	(0.00639)
indigenous	0.00984	0.00804	-0.00335
	(0.0101)	(0.0106)	(0.0112)
time t	-0.00687	-0.00506	0.00498
	(0.0242)	(0.0253)	(0.0280)
poverty x time t	0.0137	0.0179	-0.0107
	(0.0114)	(0.0134)	(0.0502)
population x time t	-8.74e-10	-1.01e-09	1.66e-08
	(8.40e-10)	(8.67e-10)	(5.13e-08)
distance Bogota x time t	-0.00000742	-0.00000818	-0.0000135
	(0.00000570)	(0.00000582)	(0.0000310)
paved roads x time t	0.0000193	-0.000000174	0.00000675
	(0.0000207)	(0.0000203)	(0.000102)
Constant	0.165**	0.155*	0.210
	(0.0714)	(0.0794)	(0.167)
Municipality, Year, and Group FE	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 28: The effect of the economic shock on mobility - Full Model Results

	Moved to gold municipality				
	(1)	(2)	(3)	(4)	(5)
Average Shock	0.0418***	0.0418***	0.0406***	0.0397***	0.0396***
	(0.0101)	(0.0101)	(0.0110)	(0.0116)	(0.0116)
time t		0.00344***	0.00297**	0.00284	0.00277
		(0.00116)	(0.00127)	(0.00191)	(0.00195)
region 2 x time t			0.000864	0.00145*	0.00145*
			(0.000708)	(0.000823)	(0.000823)
region 3 x time t			-0.000486	-0.000310	-0.000325
			(0.000770)	(0.000745)	(0.000741)
region 4 x time t			0.00110	0.000979	0.000960
			(0.000908)	(0.00124)	(0.00124)
region 5 x time t			0.000674	0.00173	0.00177
			(0.00229)	(0.00332)	(0.00332)
poverty x time t				0.000327	0.000302
				(0.00310)	(0.00311)
population x time t				1.04e-10	1.02e-10
				(2.02e-10)	(2.02e-10)
distance Bogota x time t				-0.00000147	-0.00000148
				(0.00000207)	(0.00000207)
paved roads x time t				0.00000147	0.00000146
				(0.00000802)	(0.00000802)
					(5.45e-12)
age					-0.0000509
					(0.0000428)
female					0.00242
					(0.00205)
black					-0.00251***
					(0.000933)
indigenous					-0.00268
					(0.00300)
Constant	0.00496***	-0.00364	-0.00353	-0.00318	-0.00105
	(0.00000290)	(0.00291)	(0.00290)	(0.00275)	(0.00312)
Mun, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A 29: Economic Shock and Peer Effects for fragrant captures - Cluster at Individual Level - Full Results

	Red-handed Captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.393***	0.394***	0.372***	0.379***	0.380***
	(0.113)	(0.113)	(0.115)	(0.118)	(0.118)
Average Shock	0.256**	0.256**	0.275**	0.289**	0.286**
	(0.116)	(0.116)	(0.119)	(0.123)	(0.123)
time t		0.00373	0.00382	0.00556	0.00519
		(0.0209)	(0.0210)	(0.0224)	(0.0223)
region 2 x time t			-0.00105	-0.00326	-0.00329
			(0.00226)	(0.00490)	(0.00490)
region 3 x time t			0.00177	0.000872	0.000756
			(0.00561)	(0.00566)	(0.00566)
region 4 x time t			0.000209	-0.000431	-0.000356
			(0.00376)	(0.00492)	(0.00492)
region 5 x time t			-0.00790	-0.0155	-0.0155
			(0.00736)	(0.0103)	(0.0103)
poverty x time t				0.000902	0.000913
				(0.0123)	(0.0123)
population x time t				-1.38e-09	-1.38e-09
				(9.01e-10)	(9.01e-10)
distance Bogota x time t				0.000000825	0.000000854
				(0.0000111)	(0.0000111)
paved roads x time t				0.00000890	0.00000978
				(0.0000280)	(0.0000280)
age					-0.000762***
					(0.000124)
female					-0.0188***
					(0.00268)
black					-0.00359
					(0.00409)
indigenous					0.00420
					(0.00899)
Constant	0.0634***	0.0522	0.0546	0.0467	0.0783
	(0.0161)	(0.0645)	(0.0647)	(0.0661)	(0.0662)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 30: Economic Shock and Peer Effects - Other Outcomes - Full Model

	Number of Actions ARN (1)	Number of New Returns (3)
Economic Shock	0.475	0.216*
	(0.330)	(0.110)
Average Shock	0.340	-0.0214
	(0.251)	(0.110)
age	0.00164	-0.00386***
	(0.00209)	(0.000701)
female	0.653***	-0.107***
	(0.0595)	(0.0164)
black	-0.00801	-0.0174
	(0.0502)	(0.0178)
indigenous	-0.0434	0.0339
	(0.114)	(0.0465)
time t	0.0903	0.0473
	(0.156)	(0.0571)
region 2 x time t	-0.0283	-0.00413
	(0.0234)	(0.00562)
region 3 x time t	0.0554***	-0.00486
	(0.0184)	(0.00781)
region 4 x time t	-0.363***	-0.00624
	(0.0526)	(0.00662)
region 5 x time t	0.0557	-0.00650
	(0.0364)	(0.0238)
poverty x time t	-0.0965	-0.0127
	(0.0689)	(0.0146)
population x time t	9.58e-09*	3.01e-09**
	(4.96e-09)	(1.20e-09)
distance Bogota x time t	-0.0000101	0.0000132
	(0.0000646)	(0.0000146)
paved roads x time t	0.000612***	-0.0000624
	(0.000177)	(0.0000425)
Constant	1.011***	0.251
	(0.388)	(0.172)
Municipality, Year, and Group FE	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 31: Test With Different Post-conflict Network — Full Model Results

	(1)	(2)
		Red-Handed Captures
		Peacetime group 1: (National Reintegration Office peacetime network)
Economic Shock	0.178	0.134
	(0.124)	(0.110)
Average Shock	-0.00138	0.00765
	(0.139)	(0.129)
age		-0.000879***
		(0.000193)
female		-0.0202***
		(0.00217)
black		-0.00195
		(0.00385)
indigenous		-0.00143
		(0.00647)
time t		0.00404
		(0.0116)
region 2 x time t		0.00209
		(0.00372)
region 3 x time t		-0.00480*
		(0.00280)
region 4 x time t		0.0145***
		(0.00278)
region 5 x time t		-0.00717**
		(0.00352)
poverty x time t		-0.00664
		(0.00938)
population x time t		-1.71e-10
		(5.82e-10)
distance Bogota x time t		0.00000360
		(0.00000822)
paved roads x time t		0.00000506
		(0.0000211)
Constant	0.0255*	0.0473
	(0.0145)	(0.0351)
Municipality, Year, and Group FE	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 32: Test With Different Post-conflict Network 2 – Full Model results

	(1)	(2)
		Red-Handed Captures
		Peacetime group 2: (National Reintegration Office and region peacetime network)
Economic Shock	0.155	0.133
	(0.121)	(0.117)
Average Shock	0.0123	0.0169
	(0.156)	(0.151)
age		-0.000879***
		(0.000192)
female		-0.0202***
		(0.00217)
black		-0.00195
		(0.00387)
indigenous		-0.00143
		(0.00646)
time t		0.00401
		(0.0116)
region 2 x time t		0.00209
		(0.00390)
region 3 x time t		-0.00429
		(0.00320)
region 4 x time t		0.0145***
		(0.00278)
region 5 x time t		-0.00725**
		(0.00351)
poverty x time t		-0.00651
		(0.00947)
population x time t		-1.78e-10
		(5.83e-10)
distance Bogota x time t		0.00000366
		(0.00000846)
paved roads x time t		0.00000465
		(0.0000213)
Constant	0.0262*	0.0478
	(0.0142)	(0.0346)
Municipality, Year, and Group FE	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 33: Placebo Leads of Treatment – Full Model results

	(1) R-H Captures	(2) R-H Captures	(3) Captures	(4) Captures
Economic Shock	0.00554	0.00564	0.00733	0.00611
	(0.00546)	(0.00548)	(0.00560)	(0.00536)
Average Group Shock	0.195*	0.149	0.148	0.0506
	(0.109)	(0.129)	(0.126)	(0.142)
age		-0.000826***		-0.00110***
		(0.000193)		(0.000229)
female		-0.0206***		-0.0304***
		(0.00293)		(0.00403)
black		-0.00318		0.00253
		(0.00568)		(0.00641)
indigenous		0.000914		-0.00293
		(0.0103)		(0.0150)
time t		-0.182		-0.172
		(0.180)		(0.183)
time t x poverty		0.00579		0.0169
		(0.0245)		(0.0244)
time t x population		-1.22e-09		3.11e-10
		(1.78e-09)		(2.11e-09)
time t x distance Bogota		0.0000194		0.0000221
		(0.0000215)		(0.0000217)
time t x paved roads		0.0000476		0.0000323
		(0.0000664)		(0.0000752)
time t x region 2		-0.0194**		-0.0226**
		(0.00943)		(0.00979)
time t x region 3		-0.00152		-0.0192
		(0.0105)		(0.0128)
time t x region 4		-0.00759		-0.000596
		(0.00826)		(0.0102)
time t x region 5		-0.0188		-0.0509
		(0.0241)		(0.0396)
Constant	0.0552***	0.170*	0.0605***	0.172*
	(0.0158)	(0.0891)	(0.0183)	(0.0906)
Municipality, Year, and Group FE	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 34: Main Results with Auto-correlation Tests - Full Model results

	Red-Handed Captures			
	50 kms	100 kms	150 kms	200 kms
	(1)	(2)	(3)	(4)
Economic Shock	0.385**	0.385**	0.385**	0.385**
	(0.173)	(0.177)	(0.179)	(0.175)
Average Group Shock	0.227**	0.227**	0.227**	0.227**
	(0.102)	(0.100)	(0.0951)	(0.101)
time t	0.000620	0.000620	0.000620	0.000620
	(0.00141)	(0.00122)	(0.00133)	(0.00111)
age	-0.000726***	-0.000726***	-0.000726***	-0.000726***
	(0.000159)	(0.000156)	(0.000149)	(0.000153)
female	-0.0196***	-0.0196***	-0.0196***	-0.0196***
	(0.00232)	(0.00235)	(0.00230)	(0.00183)
black	-0.00268	-0.00268	-0.00268	-0.00268
	(0.00386)	(0.00395)	(0.00385)	(0.00379)
indigenous	0.00352	0.00352	0.00352	0.00352
	(0.00839)	(0.00825)	(0.00716)	(0.00766)
Constant	-8.63e-14	-8.63e-14	-8.63e-14	-8.63e-14
	(0.000882)	(0.000850)	(0.000869)	(0.000757)
Mun, Year, and Group FE	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 35: Economic Shock and Peer Effects - Collective Crimes (all Crimes) – Full model results

	All Captures — Collective Crimes				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.370***	0.370***	0.290***	0.238**	0.239**
	(0.103)	(0.103)	(0.0986)	(0.110)	(0.110)
Average Shock	0.100	0.100	0.117	0.149	0.147
	(0.106)	(0.106)	(0.103)	(0.109)	(0.109)
time t		0.0116	0.0124	0.0242**	0.0239**
		(0.0205)	(0.0205)	(0.00936)	(0.00955)
region 2 x time t			-0.00417*	-0.00761	-0.00766
			(0.00223)	(0.00472)	(0.00474)
region 3 x time t			-0.00196	-0.00242	-0.00256
			(0.00636)	(0.00641)	(0.00640)
region 4 x time t			0.00286	0.00388	0.00396
			(0.00393)	(0.00481)	(0.00484)
region 5 x time t			-0.00131	-0.00212	-0.00210
			(0.0121)	(0.0177)	(0.0176)
poverty x time t				0.00970	0.00968
				(0.0118)	(0.0119)
population x time t				1.34e-10	1.37e-10
				(9.70e-10)	(9.73e-10)
distance Bogota x time t				0.00000740	0.00000746
				(0.0000104)	(0.0000104)
paved roads x time t				0.0000396	0.0000405
				(0.0000270)	(0.0000271)
age					-0.000820***
					(0.000151)
female					-0.0204***
					(0.00284)
black					-0.00441
					(0.00372)
indigenous					0.0105
					(0.0110)
Constant	0.0452***	0.0103	0.0130	-0.0457*	-0.0121
	(0.0145)	(0.0632)	(0.0632)	(0.0233)	(0.0241)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 36: Economic Shock and Peer Effects for Individual Crimes - Full Model Results

			Red-handed Captures — Individual Crimes		
Economic Shock	0.00907	0.00916	0.00433	0.0214	0.0215
	(0.0217)	(0.0217)	(0.0256)	(0.0303)	(0.0303)
Average Shock	0.0443*	0.0444*	0.0425	0.0342	0.0342
	(0.0257)	(0.0258)	(0.0262)	(0.0280)	(0.0280)
time t		0.00280***	0.00288***	0.00578**	0.00577**
		(0.000694)	(0.000757)	(0.00272)	(0.00273)
region 2 x time t			-0.000262	0.000895	0.000893
			(0.000607)	(0.00165)	(0.00165)
region 3 x time t			-0.00153***	-0.00155***	-0.00155***
			(0.000349)	(0.000470)	(0.000471)
region 4 x time t			0.000818	-0.000794	-0.000790
			(0.00129)	(0.00160)	(0.00160)
region 5 x time t			-0.00185***	-0.00208***	-0.00207***
			(0.000385)	(0.000647)	(0.000648)
poverty x time t				-0.00141	-0.00140
				(0.00399)	(0.00399)
population x time t				-6.07e-10**	-6.06e-10*
				(3.09e-10)	(3.09e-10)
distance Bogota x time t				-0.00000462	-0.00000461
				(0.00000404)	(0.00000404)
paved roads x time t				0.00000139	0.00000142
				(0.00000613)	(0.00000613)
age					-0.0000341
					(0.0000208)
female					-0.000780
					(0.000692)
black					0.000249
					(0.000562)
indigenous					-0.000843
					(0.000521)
Constant	0.00734**	-0.00105	-0.00128	-0.00391	-0.00253
	(0.00354)	(0.00358)	(0.00377)	(0.00402)	(0.00404)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 37: Collective Crimes (without homicides and arm possession) - Full Model Results

	(1)
	R-H Collective Crimes
Economic Shock	0.261***
	(0.0773)
Average Shock	0.236**
	(0.0918)
age	-0.000543***
	(0.000101)
female	-0.0110***
	(0.00205)
black	-0.00453*
	(0.00247)
indigenous	0.00259
	(0.00656)
time t	0.0156**
	(0.00632)
region 2 x time t	-0.00681
	(0.00434)
region 3 x time t	0.00186
	(0.00318)
region 4 x time t	0.00266
	(0.00292)
region 5 x time t	-0.00995*
	(0.00601)
poverty x time t	0.000802
	(0.00739)
population x time t	-1.11e-10
	(5.55e-10)
distance Bogota x time t	0.00000999
	(0.00000917)
paved roads x time t	0.0000179
	(0.0000190)
Constant	0.0111
	(0.0176)
Municipality, Year, and Group FE	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 38: Main Results for Non-Economic Crimes - Full Model Results

	(1) Economic Crimes	(2) Non-economic Crimes
Economic Shock	1.304	0.0354
	(1.189)	(0.0450)
Average Shock	3.168**	0.0448
	(1.501)	(0.0437)
age	-0.00367**	0.00000608
	(0.00147)	(0.0000499)
female	-0.0157	-0.00253***
	(0.0786)	(0.000885)
black	-0.0566*	-0.0000545
	(0.0336)	(0.00134)
indigenous	-0.0483	0.00557
	(0.0957)	(0.00615)
time t	0.355***	0.0112***
	(0.131)	(0.00366)
region 2 x time t	-0.0891	0.00113
	(0.0933)	(0.00272)
region 3 x time t	0.105	-0.00212
	(0.0685)	(0.00219)
region 4 x time t	-0.183**	-0.00144
	(0.0900)	(0.00184)
region 5 x time t	0.137	-0.00995*
	(0.138)	(0.00536)
poverty x time t	-0.284*	-0.00300
	(0.163)	(0.00566)
population x time t	-8.76e-09	-1.14e-09***
	(1.43e-08)	(3.51e-10)
distance Bogota x time t	0.0000832	-0.00000600
	(0.000219)	(0.00000631)
paved roads x time t	-0.000895**	0.00000599
	(0.000351)	(0.0000116)
Constant	0.0115	-0.0111
	(0.311)	(0.00713)
Municipality, Year, and Group FE	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 39: Main Results with Mobility Controls - Full Results

	(1) Historic mobility	(2) Ln Wages	(3) Mobility & wages
		Red-Handed Captures	
Economic Shock	0.471***	0.383***	0.0940
	(0.109)	(0.102)	(0.213)
Average Group Shock	0.233	0.356***	0.272*
	(0.157)	(0.127)	(0.163)
age	-0.000978***	-0.000828***	-0.000963***
	(0.000203)	(0.000160)	(0.000204)
female	-0.0230***	-0.0204***	-0.0239***
	(0.00281)	(0.00241)	(0.00292)
black	-0.00507	-0.00259	-0.00501
	(0.00496)	(0.00453)	(0.00504)
indigenous	0.00806	0.00360	0.00921
	(0.0116)	(0.0100)	(0.0120)
time t	-0.00557	0.0292	-0.496*
	(0.0228)	(0.0535)	(0.263)
moved x time t	0.0229**		0.0436***
	(0.0102)		(0.0167)
region 2 x time t	0.00239	-0.00145	0.00411
	(0.00333)	(0.00277)	(0.00333)
region 3 x time t	0.00682	0.00383	0.0108
	(0.00649)	(0.00523)	(0.00674)
region 4 x time t	0.00928	0.00205	0.0231*
	(0.00612)	(0.00595)	(0.0120)
region 5 x time t	-0.00867	-0.0144**	0.000182
	(0.00684)	(0.00683)	(0.00935)
ln wages x time t		-0.00360	0.0611*
		(0.00619)	(0.0331)
Constant	0.0279	0.0748	0.0961
	(0.0747)	(0.0640)	(0.0848)
Municipality, Year, and Group FE	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 40: Degree Centrality and Criminality - Full Model Results

	Red-handed Captures				*Total Captures*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Degree Centrality	0.0253***	0.0212***	2.684***	3.270***	0.0186***	0.0152**	3.900***	4.407***
	(0.00536)	(0.00567)	(0.248)	(0.258)	(0.00636)	(0.00672)	(0.292)	(0.304)
age				-0.00583***				-0.00503***
				(0.000576)				(0.000729)
female				-0.184***				-0.266***
				(0.0110)				(0.0147)
indigenous				-0.0735*				-0.0871
				(0.0430)				(0.0626)
black				0.0203				0.0213
				(0.0190)				(0.0234)
Constant	0.216***	0.216***	0.215***	0.449***	0.326***	0.326***	0.324***	0.535***
	(0.00480)	(0.00469)	(0.00461)	(0.0237)	(0.00590)	(0.00580)	(0.00568)	(0.0293)
Municipality and Group FE		✓	✓	✓		✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 41: Economic Shock and Peer Effects for fragrant captures - Historic Gold Production - Full model

	Red-handed Captures				
	(1)	(2)	(3)	(4)	(5)
Economic Shock	0.0154	0.0151	0.0298	0.0434	0.0407
	(0.0756)	(0.0756)	(0.0802)	(0.105)	(0.105)
Average Shock	0.0804	0.0804	0.0787	0.100	0.102
	(0.0869)	(0.0868)	(0.0926)	(0.103)	(0.103)
time t		0.0195***	0.0205***	0.0177*	0.0180*
		(0.00678)	(0.00695)	(0.00916)	(0.00935)
region 2 x time t			-0.000876	-0.00211	-0.00215
			(0.00260)	(0.00333)	(0.00334)
region 3 x time t			-0.00207	-0.00145	-0.00151
			(0.00428)	(0.00450)	(0.00451)
region 4 x time t			-0.00175	0.00385	0.00383
			(0.00331)	(0.00410)	(0.00411)
region 5 x time t			-0.00800	-0.0116*	-0.0115*
			(0.00506)	(0.00641)	(0.00639)
poverty x time t				0.0000777	-0.000119
				(0.0120)	(0.0120)
population x time t				9.41e-09	9.30e-09
				(2.01e-08)	(2.02e-08)
distance Bogota x time t				0.00000738	0.00000741
				(0.00000988)	(0.00000988)
paved roads x time t				0.0000433	0.0000441
				(0.0000305)	(0.0000306)
age					-0.000561***
					(0.000139)
female					-0.0121***
					(0.00321)
black					-0.00401
					(0.00516)
indigenous					-0.00454
					(0.00937)
Constant	0.0210***	-0.0376*	-0.0387*	-0.0433**	-0.0210
	(0.000759)	(0.0202)	(0.0203)	(0.0212)	(0.0223)
Municipality, Year, and Group FE	✓	✓	✓	✓	✓

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 42: Economic Shock and Peer Effects for Strong Ties – Full Model Results

	12 Months	18 Months	24 Months	30 Months	36 Months	42 Months	48 Months	54 Months	60 Months
gold_shock_r	0.350***	0.303***	0.317***	0.263*	0.273	0.380	0.399*	0.215	0.240
	(0.0994)	(0.115)	(0.111)	(0.156)	(0.166)	(0.238)	(0.239)	(0.287)	(0.290)
mean_gold_shock_r	0.304**	0.373**	0.365**	0.303*	0.329*	0.437*	0.446*	0.609*	0.581*
	(0.128)	(0.145)	(0.158)	(0.182)	(0.192)	(0.248)	(0.254)	(0.336)	(0.339)
age	-0.000751***	-0.000891***	-0.000922***	-0.000839***	-0.000905***	-0.000853***	-0.000705**	-0.000995***	-0.00100***
	(0.000153)	(0.000162)	(0.000170)	(0.000198)	(0.000208)	(0.000294)	(0.000297)	(0.000288)	(0.000287)
female	-0.0183***	-0.0198***	-0.0191***	-0.0193***	-0.0195***	-0.0133*	-0.0183***	-0.0186**	-0.0169**
	(0.00239)	(0.00270)	(0.00310)	(0.00388)	(0.00411)	(0.00701)	(0.00501)	(0.00723)	(0.00723)
black	-0.00231	-0.00325	-0.00265	0.00450	0.00369	0.00794	0.00757	0.0118	0.0107
	(0.00443)	(0.00465)	(0.00470)	(0.00700)	(0.00654)	(0.00803)	(0.00798)	(0.0102)	(0.0104)
indigenous	0.00660	0.00660	0.00841	0.0261	0.0264	0.0153	0.0152	0.0304	0.0299
	(0.0101)	(0.0105)	(0.0121)	(0.0210)	(0.0211)	(0.0195)	(0.0196)	(0.0267)	(0.0266)
poverty x time t	0.00142	0.00374	0.00820	-0.00779	-0.00777	-0.0240	-0.0221	-0.0205	-0.0226
	(0.0104)	(0.0127)	(0.0140)	(0.0171)	(0.0168)	(0.0236)	(0.0228)	(0.0241)	(0.0242)
population x time t	-1.26e-09	-1.28e-09	-8.63e-10	-1.64e-09	-1.62e-09	-2.59e-09*	-2.49e-09*	-2.32e-09	-2.17e-09
	(9.06e-10)	(1.05e-09)	(1.08e-09)	(1.20e-09)	(1.19e-09)	(1.39e-09)	(1.38e-09)	(1.46e-09)	(1.47e-09)
distance Bogota x time t	0.00000542	0.00000502	0.0000103	0.00000950	0.00000977	0.0000127	0.00000881	0.0000121	0.0000230
	(0.0000122)	(0.0000141)	(0.0000149)	(0.0000184)	(0.0000169)	(0.0000185)	(0.0000194)	(0.0000202)	(0.0000197)
paved roads x time t	0.0000142	0.00000808	0.00000130	-0.0000284	-0.0000290	-0.00000471	-0.00000111	0.0000485	0.0000341
	(0.0000227)	(0.0000293)	(0.0000306)	(0.0000378)	(0.0000402)	(0.0000522)	(0.0000489)	(0.0000517)	(0.0000527)
Constant	0.0836***	0.0975***	0.0848***	0.0979***	0.104***	0.128**	0.122**	0.148***	0.137**
	(0.0233)	(0.0291)	(0.0313)	(0.0359)	(0.0360)	(0.0498)	(0.0482)	(0.0564)	(0.0564)
Peer Effect	0.465***	0.552***	0.536***	0.536**	0.547**	0.535**	0.528**	0.739**	0.707**
	(0.150)	(0.162)	(0.166)	(0.243)	(0.247)	(0.253)	(0.248)	(0.319)	(0.324)
N	31,391	27,262	24,781	17,819	16,964	12,146	11,786	8,304	8,081
Mun, Year, and Group FE	✓	✓	✓	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 43: Economic Shock and Peer Effects for Weak Ties – Full Model Results

	(1) Captures	(2) Captures	(3) Captures	(4) R-H Captures	(5) R-H Captures	(6) R-H Captures
Economic Shock	0.422***	0.376***	0.379***	0.414***	0.411***	0.413***
	(0.128)	(0.135)	(0.135)	(0.0815)	(0.0904)	(0.0903)
Average Shock (Weak)	0.173	0.191*	0.188*	0.230**	0.252**	0.250**
	(0.111)	(0.105)	(0.105)	(0.0969)	(0.104)	(0.104)
time t		0.0150	0.0156		0.00657	0.00691
		(0.0210)	(0.0209)		(0.0199)	(0.0198)
poverty x time t		0.0101	0.0101		-0.000533	-0.000508
		(0.0141)	(0.0142)		(0.00815)	(0.00824)
population x time t		-1.42e-09*	-1.42e-09*		-1.55e-09**	-1.55e-09**
		(8.21e-10)	(8.27e-10)		(6.33e-10)	(6.36e-10)
distance Bogota x time t		-0.0000112*	-0.0000112*		-0.00000536	-0.00000540
		(0.00000572)	(0.00000574)		(0.00000446)	(0.00000446)
paved roads x time t		0.0000443*	0.0000451*		0.0000173	0.0000179
		(0.0000245)	(0.0000248)		(0.0000181)	(0.0000183)
age			-0.00107***			-0.000843***
			(0.000210)			(0.000178)
female			-0.0281***			-0.0194***
			(0.00264)			(0.00177)
black			0.000873			-0.00226
			(0.00407)			(0.00304)
indigenous			0.00163			-0.00109
			(0.0107)			(0.00708)
Constant	0.0656***	0.0120	0.0528	0.0614***	0.0442	0.0769
	(0.0157)	(0.0620)	(0.0612)	(0.0140)	(0.0585)	(0.0572)
Peer Effect	0.290	0.337*	0.332*	0.357***	0.380***	0.377***
	(0.178)	(0.182)	(0.182)	(0.126)	(0.132)	(0.132)
Mean of Outcome	0.0368	0.0367	0.0367	0.0368	0.0367	0.0367
S.D of Outcome	0.2071	0.2071	0.2071	0.2071	0.2071	0.2071
Observations	36,754	34,875	34,872	36,754	34,875	34,872
Mun, Year, and Group FE	✓	✓	✓	✓	✓	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 44: Regression Results for Counterfactual Experiment

	(1)
	R-H Captures (IHS)
Economic Shock	0.000741***
	(0.000164)
Average Shock	0.000966**
	(0.000387)
Constant	-0.230**
	(0.0936)
Municipality, Year, and Group FE	✓

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fixed effects for network, year, and municipality omitted because of space limitations.

Table A 45: Survey Figure Results

	(1) crime_acceptable
Aftedemo_Security	0.0985
	(0.0744)
Aftedemo_Econsecurity	-0.0896
	(0.0843)
Aftedemo_Image	0.0369
	(0.0507)
Aftedemo_friends	-0.0212
	(0.0927)
Aftedemo_socialstatus	-0.0618
	(0.0758)
Aftedemo_Adventure	-0.00762
	(0.0547)
Aftedemo_Knoledge	0.0834
	(0.155)
Aftedemo_Money	0.0677
	(0.0698)
Obligation_contact	0.0262
	(0.132)
Obligation_excombatant	0.347***
	(0.0790)
Obligation_family	0.172**
	(0.0815)
Distance_to_commander	-0.0290
	(0.0294)
Time_message_commander	-0.0320
	(0.0817)

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Fixed effects for municipality and enumerator omitted because of space limitations.