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Public healthcare financing during counterinsurgency efforts: Evidence from Colombia

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Abstract How do government counterinsurgency efforts affect local public financing during civil conflicts? We investigate this question in the context of the protracted conflict in Colombia. Using data on antinarcotics operations and health transfers from the central government to municipal governments, we employ both panel estimations and instrumental variables to address concerns of endogeneity and omitted variables. We find no clear evidence that counterinsurgency operations causally affect health transfers to municipalities. However, we find indicative evidence that counterinsurgency operations affect the dynamics of local violence. Our findings suggest that armed counterinsurgency interventions by the State should be accompanied by renewed measures to support public healthcare financing for the affected local populations; otherwise, such interventions risk exacerbating the negative consequences of conflict exposure on population health.

Key words: Intergovernmental transfers, Armed conflict, Counterinsurgency, Public spending, Antidrug policy

JEL Classifications: D74, F52, H51, H75, O15, O23

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1 Introduction

Internal conflicts have severe and long-lasting negative consequences for health and development. Population health is affected not only through the immediate effects of violence exposure on casualties and morbidity, but also – particularly in the case of protracted civil confrontations – by a complex chain of interactions between the government forces, rebel armed groups and local civilian populations. These interactions manifest themselves into longer-term consequences such as damage to public health infrastructure, reduced provision and access to healthcare by local communities, changing health and healthcare financing needs, and population displacements (Blattman and Miguel, 2010; Kruk et al., 2010).

An important element of the complex network of interactions between armed conflict actors and its population health consequences has a political economy nature. Armed insurgency, in a similar way as widespread organised crime, threatens the social contract between the State and the local population. In a bid to preserve this social contract and retain authority in their territories, national governments often undertake large-scale counterinsurgency interventions to curb the presence of illegal armed groups, disrupt their funding sources and tame their violent activities. Although counterinsurgency efforts such as large-scale military operations might contribute to weakening illegal armed groups, they might also contribute to fuel local violence, displace populations, threaten the health of civilians, and hinder healthcare and other public service provisions, with potentially wide social, political and economic consequences. For example, recent studies have shown that these government interventions may displace the financing source of armed groups (Mejía and P. Restrepo, 2016), undermine political institutions (Dube and Naidu, 2015), increase drug-related violence among traffickers (Dell, 2015) and have adverse effects on population health (Camacho and Mejía, 2017).

However, the existing evidence is not very informative about the dynamics of health systems during large-scale internal violence. In particular, we know very little about how publicly financed healthcare, which is often the only source of care access for poor populations (WHO, 2010; WHO, 2015), responds to large armed government interventions against illegal groups. As one related exception, Gupta et al. (2004) concludes that health spending as a share of GDP remains constant in conflict-affected countries, whilst public deficit tends to increase. Yet their analyses rely on cross-national aggregate data, whilst the often regional nature of internal conflicts and public financing arrangements imply that important variations in public (healthcare) financing are likely to take place at lower geographical levels. Understanding these local responses is critical to inform policies that can protect and redevelop public infrastructure, especially through guiding health financing flows to geographic areas and population groups in line with emerging health needs, thus also increasing public spending efficiency (Blattman and Miguel, 2010).

In this paper, we seek to fill some of these gaps by testing the hypothesis that through public healthcare spending, governments seek to mitigate potential adverse effects for population health of large-scale operations against illegal armed groups, also as a way of reinforcing state legitimacy locally (Bertone et al., 2019). Focusing on the case of healthcare financing transfers from the central government to sub-national governments in the protracted conflict setting of Colombia, we investigate whether counterinsurgency interventions – specifically, government-sponsored operations to disrupt drug production and trafficking activities as armed group funding sources – lead to changes in health transfers, before or after such interventions. One possibility is that the central government may anticipate surges in local healthcare demand following a counterinsurgency operation and reallocate public healthcare resources accordingly *ex-ante*, to mitigate potential adverse health effects in the local community. Alternatively, the central government might opt for cutting down their health transfers before counterinsurgency interventions in a locality, seeking to erode local support for the presence of illegal armed groups (Berman et al., 2011). Ex-post, the net result of the interaction between counterinsurgency operations and public healthcare financing will depend on the presence and magnitude of the above *ex-ante* changes in public financing, compounded by any variations in such financing after counterinsurgency interventions have taken place, for instance, to address unanticipated changes in local morbidity patterns. Therefore, the question of how government counterinsurgency interventions influence healthcare financing flows constitutes, essentially, an empirical matter.

Our key contribution to the literature is to test empirically for the existence of a causal public health financing response to counterinsurgency operations, using information at the subnational level. We analyse longitudinal data on antinarcotics operations and health-related transfers from the central government to Colombian municipalities between 2002 and 2015. To address potential endogeneity concerns in the relationship between public healthcare financing at the municipality level and the implementation of counterinsurgency operations, we adopt an instrumental variable approach based on the constructed probability that such operations are undertaken in a given municipality. We argue that this instrument is exogenous in our empirical setting and find that it is a strong predictor of the occurrence of antinarcotics operations in Colombian municipalities. We find no evidence that an increase in counterinsurgency efforts in a municipality causally lead to any significant changes in the growth of health transfers to this municipality, compared to municipalities where the frequency of counterinsurgency interventions remain unchanged. Our estimates from different econometric specifications are all tightly bounded around zero. A policy-relevant implication of the absence of such a link is that armed counterinsurgency interventions by the state should be accompanied by renewed measures to support public healthcare financing for the affected local populations; otherwise, such interventions risk exacerbating the negative consequences of conflict exposure on population health.

Our paper is organised as follows. Section 2 describes the Colombian conflict and the health system. We present the empirical strategy in section 3, discuss the data in section 4, and analyse the validity of our instrument in section 5. Section 6 presents the main results on health transfers, general public funds and local violence. Section 7 explores the treatment effect heterogeneities and section 8 concludes. Additional results are collected in an online appendix.

2 Background

2.1 Financing of the Colombian health system

The Colombian health system hinges on the provision of a universal health insurance plan that is financed by two schemes: a contributory and a subsidised regime.[1] The contributory regime is a mandatory health insurance scheme that covers all formal workers along with their dependants, and is financed by a payroll tax.[2] The poorest and most vulnerable populations are covered under the subsidised regime. The latter identifies its beneficiaries through a proxy-means test index based on the socio-economic conditions of each household, and standardised at the national level.[3] The Fund of Solidarity and Assurance (FOSYGA) collects all payroll contributions of the contributory regime as well as public funds raised through general taxes, and redistributes the pooled funds mostly between the contributive and the subsidised regimes (Camero Nader et al., 2016).[4].

The national government funds, known as *Sistema General de Participaciónes* (General System of Participation, SGP) are divided into four categories: health, education, water and sanitation, and other general purposes. The health component of SGP are public resources allocated to the solidarity sub-account of FOSYGA (subsidised regime), public health (about 10%) and the poor population unaffiliated to a health insurance scheme.[5] Together, SGP and FOSYGA account for more than 90% of public health spending (Calderón et al., 2011). Additional funds provided by the department and

[1] An additional special social security scheme also exists which covers teachers in public schools and universities, the military and police officers, and workers of the national oil company. The special regime covers about 5% of Colombia's population.

[2] The contributory regime also includes self-employed and those with financial capacity to pay (Camero Nader et al., 2016).

[3] The calculation of the index score relies on information collected through frequent household surveys administered by municipalities.

[4] The fund FOSYGA designates as Compensation and Solidarity the sub-accounts which relate to the contributory and subsided regimen respectively, so as to distinguish between the in-flow and out-flow of funds. More than 90% of the pooled funds are allocated to the compensation and solidarity sub-accounts of the FOSYGA. The remaining funds are used for health promotion activities and cover catastrophic illnesses and traffic accidents (ECAT).

[5] The national government devotes funds to general public health strategies through transfers to local governments (departments, municipalities and districts). Note also that SGP accounts for two-thirds of the national government health budget, the remaining resources being allocated to the health sector mainly by the Ministry of Defence (military hospitals) and the Ministry of social protection (Núñez et al., 2012).

municipality's own resources are devoted to public health and the unaffiliated poor population. Public healthcare spending represents about 80% of total health expenditures in Colombia (OECD, 2015). Since SGP is the discretionary part of public healthcare funding allocated by the government, our analysis focuses on understanding its variations with respect to counterinsurgency efforts.

2.2 The Colombian armed conflict

The roots of the long lasting armed conflict in Colombia can be tracked back to the episode of "La Violencia", a bipartisan conflict that turned into a civil war between 1948 and 1958, claiming the lives of more than 160,000 people (L. A. Restrepo, 1992). The conflict ended with a pact to share control over the state between the two major parties, Liberals and Conservatives. This elite arrangement excluded any other political forces and contributed to the rise of left-wing guerrilla movements such as the Armed Revolutionary Forces of Colombia (FARC), claiming their right to participate in the public space. Although the pact ended in 1974, tensions between the state and the guerrillas continued to increase and the prominent role of the FARC in some territories triggered the creation of a self-defence movement, formed of local private armies, that arose to fight the guerrilla groups in territories abandoned by the state, and ultimately intensified the conflict. In the meantime, the transformation of the country into an illegal crop producer created an opportunity of rent-extraction for non-state actors (Durán-Martínez, 2017). Both guerrillas and paramilitaries were often found to have links with the control, production, and trafficking of cocaine. They have also both been accused by international human rights organisations of massacring civilians. The alarming levels of political and drug-related violence generated by the armed conflict between the state, guerrillas, and paramilitaries have put local communities in constant danger, with none of the actors able to guarantee their security (Arias and Goldstein, 2010). In addition, limited access to healthcare in conflict-affected areas is likely to have exacerbated the detrimental effects of forced displacements and exposure to violence on population health (Franco et al., 2006; Kreif et al., 2020).

Since 2000, collaborative efforts between the United States and Colombia have aimed to combat the production and trafficking of drugs under "Plan Colombia", a programme originally designed to improve the socio-economic instabilities in Colombia, but which has rapidly evolved into a military initiative to address both drug trafficking and rebel armed groups. In this counterinsurgency war against guerrilla movements, the security forces primarily targeted the FARC. The United States government spent close to $10 billion dollars between 2000 and 2015 for Plan Colombia whilst the Colombian counterpart disbursed over $85 billion dollars during the same period (figure 1).[6] During Álvaro Uribe's presidency (2002-2010), the United States and Colombian governments merged drug enforcement with counterinsurgency operations to fight the FARC and regain state control of territory through military presence.[7] The paramilitaries, while maintaining close ties with drug trafficking, benefited from tacit support by the military which strategically depended on them to maintain control of areas that the paramilitaries dominated. These circumstances also provided opportunities for the paramilitaries to increase their territorial and political influence by exploiting the vacuum left behind the FARC who were targeted by Plan Colombia (Dube and Naidu, 2015), including through enhanced influence in local elections (Acemoglu et al., 2013).

The results of Plan Colombia on drug trafficking are controversial (Mejía, P. Restrepo, and Rozo, 2017), as cocaine production and violence remained high before the 2016 peace agreement, although certain types of violent crimes like kidnappings decreased substantially. Counterinsurgency operations might have improved healthcare provision, access and governance through the reduction of drug trafficking and armed group presence (Berman et al., 2011); but they might also have had adverse effects on access to public services (including health centres) and increased the local levels of conflict violence after the implementation of these counterinsurgency operations (Camacho and Mejía, 2017).

[6] Information on the United States security and defense assistance in Colombia was obtained from Security Assistance Monitor (https://securityassistance.org/colombia) The yearly spending of the United States to reduce illicit narcotics and improve security reached up to $ 1.6 billion dollars in 2008; for Colombia, data was collected from the Ministry of Defense.

[7] An estimated 15% of Colombian municipalities had no police presence before 2002 (GAO, 2008).

2.3 Cocaine seizure

Cocaine is obtained through a series of transformations between its harvesting from local farmers to its trafficking and trading in the international market (Umpierrez et al., 2016). Farmers either directly sell coca leaves or transform them into coca paste through a chemical process that extracts coca from the leaf.[8] Coca paste is then traded among drug traffickers, transformed into cocaine hydrochloride in clandestine laboratories, and eventually smuggled into foreign countries (North America and Europe).

Under Plan Colombia, the counternarcotics operations consisted of manual eradication, aerial spraying, seizures of drugs and precursors used in the transformation process of coca and the destruction of cocaine processing laboratories (GAO, 2008). Aerial eradication received by far the largest portion of the United States aid package as it involved the purchasing and maintaining of helicopters that stationed around the country. Aerial spraying was specific to coca producing regions and might not have affected the control of armed groups over the sprayed territory, leaving the level of exposure to violence unchanged among local populations. However, the herbicide used in aerial spraying had direct detrimental effects on health outcomes (Camacho and Mejía, 2017).

3 Empirical strategy

3.1 Municipality fixed-effects estimation

The relationship between counternarcotics operations and the flow of government health transfers to municipalities can be described by

$$\Delta ln(SGP_{mdt}) = \beta Antinarcotics_{mdt} + \mathbf{X}^{'}_{mdt}\gamma + \alpha_m + \lambda_{dt} + \varepsilon_{mdt} \tag{1}$$

where $\Delta ln(SGP_{mdt})$ denotes the growth rate of public healthcare spending in municipality m, department d and year t. The variable of interest, $Antinarcotics_{mt}$ measures

[8]Because it takes about one ton of coca leaf to produce one kilogram of coca paste, the latter form is more convenient for trafficking purpose. Coca is therefore often transformed into paste within coca producing sites.

antinarcotics interventions captured by the quantity of cocaine seized in municipality m in year t. Since the distribution of cocaine seizure is highly skewed with many municipalities reporting zero seizure, we transform the variable using the inverse hyperbolic sine function introduced by Johnson (1949). The function is similar to the natural logarithm transformation but is defined at zero.[9] Alternatively, we also use the logarithm transformation by adding 1 to coca seizure and we minimise the impact of this addition by expressing the variable in grams. The coefficient of interest, β, expresses the change, divided by 100, in the growth rate of health transfers associated with a one percent increase in antinarcotics interventions. That is, a 1 percent increase in coca seizure raises the growth rate of SGP by $\beta/100$.

We argue that cocaine seizure should be a strong proxy for antinarcotics interventions. First, under Plan Colombia, data on the estimated kilograms of cocaine seized was one of the main indicators used to evaluate the performance of counternarcotics efforts, along with the hectares of coca eradicated (GAO, 2008). As presented in section 2, cocaine paste and hydrochloride are the two forms used for trafficking and distributing the drug on the illegal market. We exclude the seizure of coca leaf that is mostly present in coca producing regions and which reflects farmers engagement in illicit farming rather than insurgent activities.[10] Second, under Plan Colombia, counternarcotics operations were largely assimilated to counterinsurgency efforts against the FARC (LeoGrande and Sharpe, 2000). Third, drug seizure is typically made by the municipal police and the military.[11] As the Police forces are under the jurisdiction of municipalities, cocaine seizure varies at this administration level. Mayors might have therefore a discretionary control over the intensity of counterinsurgency operations.

The vector $\mathbf{X}_{mdt}$ denotes the vector of time-varying municipality covariates that are

[9] In particular, $asin(x) = ln\left(x + \sqrt{x^2+1}\right)$. When x is large enough, the interpretation of the coefficient is similar to the logarithm transformation as it approximates as $ln(2) + ln(x)$. For this reason also, the results are practically unaffected if we use the inverse hyperbolic transformation of our dependent variable SGP_{mdt} and consider its growth rate.

[10] Importantly, the production of coca leaf by farmers can simply result from the need for a livelihood. Hence, seizing coca leaf might not directly threat drug traffickers and affect the conflict.

[11] On the other hand, operations related to aerial spraying and dismantlement of coca-producing laboratories pertained to the military forces or the Anti-narcotic police, and these operations are decided at the national level.

thought to be correlated with both the outcome and the explanatory variable of interest. We include the ratio of affiliates to the subsidised regime among the total population in municipality m, since the government health transfers primarily target those affiliated to the subsided regime. We also control for the total yearly population in each municipality and the rurality to capture the potential effects of socio-economic factors. We also account for the possibility that right-wing mayors with large electoral support may influence health transfers when aligned with President Uribe's coalition, by interacting a time dummy equal to one during Uribe's presidency (2002-2010) with mayoral outcome results. Likewise, we control for the interaction of mayoral outcome with an indicator equal to one if the incumbent governor of the department belongs to the right-wing coalition party. Additional controls for municipality characteristics include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, and which are all interacted with year dummies. Municipality fixed effects, α_m, account for time-invariant municipality characteristics, such as local administrative capacity. Since department governors have the political power to take decisions that affect various factors at the municipality level, we also add department-year fixed effects, λ_{dt}, to partial out any general yearly variations in health transfers that may vary across departments. We cluster standard errors at the municipality and department-year level.

3.2 IV strategy

The main threat to interpret the estimate of β as the causal impact of antinarcotics operations on municipality health transfers is the potential endogeneity of these operations. Some omitted factors, such as financial downturns, could simultaneously reduce counternarcotics efforts and decrease public health spending through an overall reduction of the government budget, creating thereby a spurious correlation between the two variables. Additionally, the national government can prioritise drug enforcement efforts in municipalities with higher provision of public services to ensure that public resources are not controlled by non-state actors. This reverse causality could lead to an upward bias on our estimates. Another threat to the identification strategy is that health care needs might correlate with both counternarcotics operations and omitted time-varying municipality characteristics.

We address this potential endogeneity concern by constructing an instrumental variable that is associated with antinarcotics operations but is uncorrelated with the growth rate of health transfers. Specifically, we use the growth rate of U.S. aid military expenditures to reduce illicit drug trafficking, interacted with a constructed probability that drug enforcement operations take place in a municipality. As highlighted in the background section, the US government has historically had a tremendous influence on the Colombian government's strategy against drug trafficking and rebel armed groups. Under Plan Colombia, US military aid assistance provided considerable financial support for the state to regain control over territories with a high presence of guerrillas groups, and improve security. Further, we use the frequency of antinarcotics operations over the 2002-2015 period to exploit variation across municipalities and construct the probability of antinarcotics interventions. We define $Coca_{mdt}$, an indicator equal to one if antinarcotics operations took place in municipality m, department d and year t. The probability, $ProbaCoca_{mdt}$, that an antinarcotics operation occurs in municipality m over the sample period is simply the average number of years that a municipality hosts an operation.[12] By interacting US military aid assistance specifically targeting counterinsurgency operations with the probability of occurrence of such interventions, we increase the strength of our instrument. Our interacted instrument is as follows

$$ProbaCoca_{mdt} \times USExpen_t = \frac{1}{14} \sum_{i=2002}^{2015} Coca_{mdi} \times USExpen_t \tag{2}$$

where $ProbaCoca_{mdt}$ denotes the probability of antinarcotics interventions in municipality m, department d and year t, and $USExpen_t$ is the time-varying growth of US expenditures for reducing illicit Narcotics and Improving Security at the national level (henceforth US military aid assistance).[13] We discuss the validity of the instrument in

[12]We follow Nunn and Qian (2014) and Ahmed (2016) who, in a different analytical context, proxy the probability of receiving aid by the average number of years that aid is received in the country over the sample period.

[13]In 2007, US military aid assistance reached \$ 1.6 billion dollars (expressed in 2015 USD), which corresponds to an increase of \$ 325 million dollars or nearly 50% from the averaged US military aid

section 5.

The first-stage equation is given by:

$$Antinarcotics_{mdt} = \delta(ProbaCoca_{mdt} \times USExpen_t) + \mathbf{X}'_{mdt}\gamma + \alpha_m + \lambda_{dt} + \nu_{mdt} \quad (3)$$

Our instrument captures the effects of changes in US military aid assistance with respect to the probability of antinarcotics interventions in municipalities. If the operations are effective, we would expect that their marginal benefit on fighting drug-trafficking reduces with their intensity. For example, high frequency of interventions may weaken and divert local trafficking (Dell, 2015), and reduce the possibility to seize additional quantities of illegal drugs. As the growth of US military aid assistance increases, the probability to seize cocaine over the sample period may increase but the seized quantities decrease. In other words, we anticipate the coefficient δ to be negative.

We assess the robustness of our results by using the marginal outcome of right-wing parties in the mayoral elections, instead of the probability of antinarcotics interventions. The intuition is that municipalities with right-wing mayors who show active support for military interventions against drug trafficking and rebels may be more likely to host antinarcotics operations. We discuss in details the validity of this alternative instrument in the online appendix B.

Figure 2 provides a visualisation of the geographic distribution of the probability of counterinsurgency operations over the 2002-2015 period. Municipalities without any operations over the sample period appear in blue, and we classify the distribution of the probability of interventions by quartile, using white and grey for the first two quartiles of the distribution and dark grey and black for the third and fourth quartiles. The figure illustrates that urban municipalities with high population density (in the centre of Colombia) are less likely to be affected by antinarcotics operations than remote rural

assistance allocated to Colombia prior to this year (figure 1), before returning to its average level after 2007. This sharp increase illustrates the presence of exceptional expenditures during this year, such as the provision of helicopters and army aviation support for aerial spraying (GAO, 2008). Since we exclude aerial spraying activities from our analysis, this increase may significantly bias our results. Because we could not distinguish which sum was specifically devoted to the aerial spraying program, we chose to exclude year 2007 from our analysis.

municipalities (in the South and North).

4 Data

4.1 Government health transfers and other variables

We collect information from the National Planning Department (NPD) on government health transfers SGP to municipalities, containing data on the contributory and subsidised health insurance schemes, from the Ministry of Health.[14] We also gather information on the population affiliated to each health insurance scheme from this same data source, as well as data on other government public transfers SGP to municipalities. We supplement this data with information from the NPD on public expenditures, estimated municipality GDP, dependence on government transfers, debt, investment, municipality resources and saving capacity at the municipality level.[15] Additional information on municipality characteristics include population, rurality index, distance to capital, number of health centres or hospitals in the municipality, presence of oil and/or mineral resources, and are all obtained from the Centro de Estudios sobre Desarrollo Económico (CEDE) in the Facultad de Economía at the Universidad de Los Andes. The dataset covers all 1,098 Colombian municipalities between 2002 and 2015.

4.2 Explanatory variable: antinarcotics operations

We capture antinarcotics operations by the quantity of cocaine seized in municipalities, collecting yearly data on the quantity of illicit drugs seized in a municipality from the National Police of the Ministry of Defence and the *Observatorio de Drogas de Colombia*. We expect this variable to capture municipality-level and time variation in the intensity of counterinsurgency operations, because drug seizure is typically made by the municipal police and the military, and police forces are under the jurisdiction of municipalities.

[14] The data are obtained from *Sistema Integrado de Información de la Protección Social* (Integrated information system of social protection, SISPRO).

[15] The estimation of municipality GDP is produced by the NPD using municipal budget execution (https://www.dnp.gov.co/programas/desarrollo-territorial/Paginas/ejecuciones-presupuestales.aspx)

We create a cocaine seizure variable that combines the yearly seizures of the two forms of cocaine used for trafficking and distributing the drug on the illegal market: cocaine paste and hydrochloride. We exclude the seizure of coca leaves that is mostly present in coca producing regions, and which reflects farmers engagement in illicit farming rather than insurgent activities.

4.3 Instrumental variables

4.3.1 US military aid assistance

Our main instrument uses information from the U.S. funding for reducing illicit Narcotics and Improving Security. The funding relates to the US financial support to Plan Colombia that started in 2000. Data about the U.S. Assistance for Colombia by the State Department Foreign Aid account comprises the following items: 1) International Narcotics Control and Law Enforcement (named Andean Counterdrug Program between 2000 and 2009); 2) Nonproliferation, Anti-Terrorism, Demining, and Related Programs; 3) Foreign Military Financing; 4) Combating Terrorism Fellowship Program and 5) Aviation Leadership Program. Many of these categories of US aid assistance refer to general purposes that can be hard to relate to counterinsurgency activities. To increase the predictive performance of our instrument, we restrict US military aid assistance to the first category above. We obtained this data from Security Assistance Monitor and supplemented it with reports from the Congressional Research Service on Colombia between 2002 and 2015 (see appendix A for more details on data source and definition of the variables).

4.3.2 Political outcomes

We also use the results of the mayoral elections as an alternative instrument for the implementation of counterinsurgency operations.. Electoral outcomes at the municipality level come from the National Registry of Civil Status and have been compiled by CEDE in the Facultad de Economía at the Universidad de Los Andes. We obtained electoral outcomes for the 2000, 2003, 2007, and 2011 municipal elections along with information on the name and party affiliation of each candidate.

5 Validity of our main instrument

We build on recent econometric work on Bartik instruments that lay out the sufficient identifying conditions, in our setting, to estimate the causal effect of antinarcotics operations (Adao et al., 2019; Borusyak et al., 2020). By interacting national level shocks in US military aid assistance with the probability of antinarcotics operations, our instrument exploits national fluctuations in the growth of US military aid assistance as shocks for local operations, and the probability of operations represents the share, or the importance, of drug enforcement policies in a particular municipality within the national context.[16] The probabilities of operations are local measurements that capture differential exposure to the shocks, and the identification comes from changes in the likelihood of operations between similar municipalities that should differentially affect the changes in the growth of health transfers.

By leveraging exogenous shocks on national US military aid assistance, we allow for the probability of cocaine seizure to be endogenous. The heterogeneity in the likelihood of cocaine seizure across municipalities creates differential exposure to random shocks of US military aid assistance that are common among municipalities. Importantly, each shock is assumed to be not only exogenous but also uncorrelated with the bias introduced by the probability of cocaine seizure. The validity of the instrument relies on the repetition of these exogenous shocks which ultimately reduce the bias towards zero on average and, thereby, ensure the consistency of the interacted instrument (Adao et al., 2019; Borusyak et al., 2020). The identifying assumption is that the differential effect (e.g. between two municipalities) of a common shock to the growth of US military aid, on the probability of antinarcotics operations, only affects the change in the growth of health transfers through antinarcotics operations.

Hence, the validity of our strategy rests upon the excludability of changes in US

[16] Example of studies that use a Bartik instrument, also known as shift-share instrument, in a similar setting include Werker et al. (2009), Nunn and Qian (2014) and Ahmed (2016).

military aid assistance. Here, the main concern is that the growth of US military aid assistance could be indirectly associated with changes in the Colombian public healthcare budget. For example, the Colombian government could decide to reallocate more resources to the health sector following an increase in US military aid, or increase the military budget and reduce the share of public health resources. Whilst we cannot completely rule out this possibility, yearly changes in overall resources devoted to the national health budget should be absorbed by the department-time fixed effects (or year fixed effects when we simply include them in the regression). Concerns would therefore only arise if changes in US military aid assistance affect the geographic distribution of healthcare resources over municipalities. Although little information exists on the decision-making process of the allocation of US military aid assistance, it is fair to expect that the allocation decision is based on national levels of insecurity and drug trafficking in Colombia rather than in specific municipalities (GAO, 2008). It is thus highly unlikely that the Colombian government systematically changes health transfers to those municipalities targeted by US-supported strategies following a change in the growth rate of US military aid assistance.

Nonetheless, we address these challenges and the overall validity of our instrument in table 1. The table reports the coefficient estimates on the interacted instrument from the first-stage equation (3), along with the partial F-statistic. Column 1 only includes municipality and year fixed effects and column 2 of table 1 adds the baseline controls described in the previous section. In both cases, the F-statistics are very high and the coefficient estimates similar. From columns 3 to 6, the inclusion of department-year fixed effects reduces the coefficient estimates on the instrument and its predictive power, but the F-statistic remains well above the conventional threshold of 10.

In column 4 of table 1, we account for the possibility that municipalities with high rebel presence drive the correlation between our instrument and antinarcotics operations, if US military aid assistance specifically targets those municipalities. We exclude municipalities from the departments where the state had little presence during the 2002-2015 period (Putumayo, Caqueta, Guaviare and Meta), which are mostly located in the South, and were historically used as primary locations for the guerrillas to establish their influence. However, the coefficients remain very stable and highly significant, indicating that the correlation between the instrument and antinarcotics operations is not driven by municipalities with a comparatively higher rebel presence.

Column 5 of table 1 explores whether the period during Uribe's presidency (2002-2010), characterised by a strong emphasis on military interventions against rebels, could differentially affect the results. For example, President Uribe could have had a higher influence on US military aid assistance through his political strategy, resulting in omitted variables bias. The coefficient estimates remain virtually unchanged and the F-statistic does not increase its power, confirming that the instrument correlation with antinarcotics operations is not driven by the Colombian central government's influence.

We also explore robustness in column 6 by including the lagged version of the instrument. Finally, we provide a falsification test in column 7 where we estimate the coefficient on the interaction between the probability of cocaine seizure and the growth of Official Development Assistance (ODA) from the US to Colombia, obtained from the OCED Creditor Reporting System database. Reassuringly, the coefficient is statistically insignificant and close to zero, thereby confirming the importance of the growth of US military aid assistance in predicting antinarcotics operations.

Overall, the tests performed in this section demonstrate that our instrument has strong power for predicting variations in antinarcotics operations, and that the power of the instrument relies both on the growth of US military aid assistance and the probability of counterinsurgency interventions.

6 Results

6.1 Health transfers

Table 2 provide summary statistics for all key variables used in the analysis at the municipality level. It shows that municipality health transfers grew by 3% on average during the study period whilst US military aid assistance decreased by 9%. The probability that a municipality hosts an antinarcotics operation in a given year is 51% but large disparities exist across municipalities in Colombia, as highlighted in figure 2. Figure 3 provides a visual inspection of the relationship between municipality health transfers and antinarcotics operations. The figure plots the 3-year moving average of the growth rate of SGP (red line) and the 3-year moving average of the logarithm of cocaine seizure (in grams). It suggests the absence of a clear relationship pattern: whilst antinarcotics operations grow steadily across the sample period, the average growth rate of SGP fluctuates between 2 and 4% during the same period.

Table 3 reports the baseline estimates for the effect of counterinsurgency operations on government health transfers. We report the estimates of the coefficient of the coca seizure variable using both the Inverse Hyperbolic Sine (IHS) and log-transformation. The first four columns present the results from the fixed-effect (FE) estimation of equation (1). Columns (1) and (2) only control for municipality and year fixed effects to provide a benchmark, and we fully control for the baseline covariates in columns (3) and (4). The fixed-effect estimates suggest a small, positive but statistically insignificant correlation between government health transfers and counterinsurgency operations once we control for the main covariates. The results are quantitatively similar between the natural log and inverse hyperbolic sine transformations.

Columns (5) to (10) of table 3 present the second-stage of the two-stage least squares (2SLS) estimates in panel A, and their corresponding first-stage estimates in panel B. As in columns (1) and (2), columns (5) and (6) only control for municipality and year fixed effects, and columns (9) and (10) control for department-year fixed effects. For completeness, columns (7) and (8) also report the estimates when fully controlling for the baseline covariates but with year fixed effects. The coefficients on antinarcotics operations are again small and positive, but the introduction of department-year fixed effects changes the sign of the 2SLS estimates. In panel B, the Kleibergen-Paap F-statistic for the excluded instrument is around 24 for both instrumented variables (logarithm and inverse hyperbolic sine transformations) when we fully control for the covariates in columns (9) and (10), suggesting that the instruments remain strong predictors of cocaine seizure. The results show that there is a strong negative correlation between the interacted term of probability of cocaine seizure and the growth of US military aid assistance, and cocaine seizure. Specifically, a one percent increase in both the probability of cocaine seizure and the growth of US military aid assistance decreases cocaine seizure by more than 4 %.

The magnitudes of the coefficients of coca seizure are larger with the 2SLS specifications than with the FE models, and become negative but statistically insignificant once we fully control for the baseline covariates. Whilst the endogeneity of coca seizure might induce a downward bias in the FE estimates, other factors may contribute to the large difference in the coefficient estimates. One possibility is measurement errors in the cocaine seizure variable that could introduce further downward bias in the FE estimates. Sources of measurement error could include i) under-reporting of cocaine seizure, both in terms of quantity and frequency, by Police and military officials; ii) combined data may become inaccurate or outdated once centralised by the Ministry of Defence if there exist discrepancies between the data possessed by the municipalities and the information transmitted to the central government.[17] Another likely explanation for the difference between FE and 2SLS estimates is that the latter are capturing a local average treatment effect (LATE). Antinarcotics interventions may have a different effect among municipalities with regular interventions (complier municipalities), compared to municipalities with a lower probability of interventions but potentially higher intensity of coca seizure. For example, complier municipalities might be under closer watch of the government than noncomplier municipalities. We control for municipality characteristics such as distance to the capital or whether the municipality hosts oil or mineral production sites, that we interact with year dummies. Nonetheless, other unobservable characteristics might correlate with the government's closer attention to particular municipalities, which in turn might be correlated with health transfers.

The magnitudes of the 2SLS estimates suggest that increasing antinarcotics operations in a given municipality from 0 to the 50th percentile of the sample (a 3.0 kg increase in coca seizure) leads to a rise in the growth rate of municipality health transfers of $ln(3000) * 0.007 = 0.08$ percent, when fully controlling for the baseline covariates with year fixed effects, and a decrease of $ln(3000) * 0.007 = 0.05$ percent when controlling

[17]Measurement errors could correlate with department and municipality's characteristics, such as administrative capacity or corruption. By controlling for municipality and department-year fixed effects, we should account for most of this potential correlation.

for department-year fixed effects. Although with opposite sign, these results are both quantitatively small and statistically insignificant, and thus suggest that health transfers are not systematically affected by counterinsurgency operations.

6.2 General public transfers

The central government may choose to mitigate the effect of antinarcotics operations on population health and well-being through other general public transfers to municipalities. Since the provision of general public services could have spillover effects on population health (e.g. road access to hospitals, sanitised water, availability of electricity in health facilities), we investigate how antinarcotics operations affect the general transfers of the central government to municipalities. To do this, we use data on total public transfers (SGP) that comprise transfers for education, drinking water and sanitation, and general purposes, as the dependent variable in equation (1), and we subtract from it health transfers. Table 4 presents the effect of antinarcotics operations on total public transfers using 2SLS. Column 1 reports the contemporaneous estimates, and columns 2-3 show the lagged and lead estimates respectively. In all regressions, we find a positive but quantitatively small and statistically insignificant relationship.

6.3 Local violence

Finally, we explore in table 5 the effect of antinarcotics operations on local violence. The table reports the results from our baseline 2SLS estimation where the dependent variable is the number of homicides in columns (1) and (2), and the number of acts of war in columns (3) and (4).[18] Both variables are taken in natural logarithms. Columns (1) and (3) provide the estimates for the contemporaneous effect of antinarcotics operations, and columns (2) and (4) report the estimates of the lagged effect. All estimations control for our full set of baseline covariates. The results suggest that antinarcotics interventions have a mixed effect on local violence. On the one hand, they tend to reduce

[18]We collect data on the number of acts of war and the number of homicides from the Central Institute for Memory and Truth Reconstruction (CNMH) and the National Victims Registry (RUV) respectively. Acts of war are acts that are carried out by the actors of the armed conflict with a defined military objective and using illicit means and weapons in combat (CINEP, 2008).

contemporaneous acts of wars but increase them in the following year in a similar magnitude. On the other hand, we find that antinarcotics interventions reduce significantly the number of homicides in the year following the operation but have no statistically significant effect on the contemporaneous number of homicides. These results are indicative that drug enforcement operations can indirectly affect the local public health system, by inducing temporal variations in the risk and intensity of violence exposure within local communities.

6.4 Robustness checks

In this section, we conduct extensive tests to demonstrate the robustness of our findings.

6.4.1 Potential remaining reverse causality

We start by addressing potential concerns of omitted variable bias in equation (1) that could arise if the growth rate of past municipality health transfers continues to affect the growth rate of contemporaneous transfers. Table 6 explores this possibility by providing the 2SLS estimates of equation (1) while controlling for the lagged growth of health transfers. Columns (2) and (3) contain one lag of the growth of health transfers, and columns (4) and (5) include three lags. Column (1) reports the baseline 2SLS estimates for comparison. To minimise the econometric problems in estimating models with lagged dependent variables (Nickell, 1981), we present two sets of results by first, excluding municipality fixed effects from the 2SLS estimations (columns (2) and (4)), then including them (columns (3) and (5)). Because excluding fixed effects poses a risk of omitted-variables bias, the true effect can be recovered from the coefficient estimates between the two specifications (Angrist and Pischke, 2008). Controlling for the growth rate of SGP results in a slightly increased point estimate for the effect of antinarcotics operations compared to our baseline model, but the results remain qualitatively unchanged.

6.4.2 Dynamic effects of antinarcotics operations

A concern may arise if antinarcotics operations are more likely to affect the growth rate of SGP in the next period rather than in the contemporaneous period. That is, upon observing a change in health needs after drug enforcement efforts, the government decides to adjust its health transfers. Alternatively, the government might anticipate changes in future health needs and alter health transfers prior to antinarcotics operations. To analyse the dynamic effects of antinarcotics operations, we extend the basic model (1) by including additional lags and leads of the antinarcotics operations, and, for the 2SLS estimation, we instrument these with the lagged versions of the instrument used before. Figure 4 presents the FE estimates on antinarcotics operations (blue dots) from equation (1) augmented with four lags and four leads, along with the 95% confidence intervals (grey lines). The figure confirms that past or future changes in drug enforcement operations are not associated with changes in contemporaneous municipality health transfers, except for the first lag of the antinarcotics operations variable that provides an ambiguous result. Thus, we further investigate the dynamics in table 7 which provides the FE and 2SLS estimates of only the first lag and lead of the antinarcotics operations variable in panel A, with the first-stage estimates being presented in panel B. The FE and 2SLS results are reported in columns (1) and (2) and columns (3) and (4) respectively. The results are similar between lagged and contemporaneous antinarcotics interventions: the lagged instrument, presented in column (3), has a stronger predictive performance for cocaine seizure but the results remain negative and statistically insignificant. On the other hand, the 2SLS estimate of the lead of antinarcotics operations is positive and statistically significant. Nonetheless, the effect is quantitatively small: an increase in municipality's antinarcotics operations from 0 to the 50th percentile of the sample is associated with a rise in municipality health transfers by $ln(3000) * 0.01 = 0.08$ percent.

Figure A1 in the online appendix provides additional evidence of the stability of the results during the study period. The graph plots the coefficients on the interaction term between antinarcotics operations and yearly dummies obtained from our baseline 2SLS models, revealing positive but insignificant effects between 2003 and 2015. Specifically, the coefficient estimates appear very stable and we do not find evidence that the change from Uribe to Santos as Colombian president in 2010, or the regional and municipal elections every four years between 2003 and 2015, affect our baseline results.

6.4.3 Alternative instruments

We next present evidence that our results are robust to alternative instruments. First, we consider a one-year lagged growth rate of US military aid assistance interacted with the probability of cocaine seizure. We aim to explore whether the lagged instrument has a better predictive performance for contemporary antinarcotics interventions than our baseline (contemporaneous) instrument. Column (1) in table 8 presents the 2SLS estimates with the lagged instrument. The results indicate that the new instrument has less predictive power for cocaine seizure and results in lower coefficient estimates from the first-stage equation than with the contemporaneous instrument. We again find no relationship between cocaine seizure and municipality health transfers, but because this weaker instrument might bias the second-stage estimate, we only consider this result as informative.

Second, we further test the validity of our baseline results by constructing an alternative instrument based on municipal election outcomes. Specifically, we exploit the support for military actions by Uribe's coalition parties to predict the occurrence of antinarcotics interventions. We define the marginal outcome of the right-wing party in a municipal election as the difference between the vote share of the right-wing coalition party and the highest vote share among non-right-wing candidates.[19] A negative marginal outcome therefore indicates that the right-wing candidate lost the election.

The municipal election years that span our sample period are 2003, 2007 and 2011. Since the marginal outcome of the mayoral elections only varies across municipalities every four years, there might exist a high degree of collinearity with municipality fixed effects. As with our main instrument, we thus interact right-wing marginal outcome with

[19] We follow the methodology described in Fergusson et al. (2020) to define the right, centre, and left-leaning parties, and we supplement it with information from `congresovisible.org`. We define right-wing parties as those that belong to Uribe's coalition (*Alianza Uribista*) and those that expressly support the use of force against guerrilla groups. We also include as right-wing parties those that have had links uncovered with paramilitary organisations from searches in local or national newspapers.

the growth rate of US military aid assistance. The first-stage equation is given by:

$$Antinarcotics_{mdt} = \delta(RightMargin_{mdt} \times USExpen_t) + \mathbf{X}'_{mdt}\gamma + \alpha_m + \lambda_{dt} + \nu_{mdt} \quad (4)$$

where $RightMargin_{mdt}$ denotes the marginal outcome of the right-wing party in municipality m, department d and year (election) t, and $USExpen_t$ is the time-varying growth rate of US expenditures for reducing illicit Narcotics and Improving Security at the national level. The interaction term captures any differential effects that the right-wing marginal vote in municipal elections has on antinarticotics operations, depending on the yearly growth rate of US military aid assistance. We, therefore, expect the coefficient δ to be positive.

In section B of the online appendix, we provide evidence about the correlation of the instrument with the endogenous variable, as well as support for the validity of the exclusion criteria.

Columns (2) to (4) of table 8 (panel A) report the results from the 2SLS estimation, and the corresponding first-stage estimates (panel B). Column (2) uses the instrument that interact right margin outcome with the contemporaneous growth rate of US military aid assistance; columns (3) and (4) report the results when using the lagged and lead growth rates of US military aid assistance, respectively, in the interaction term. The Kleibergen-Paap F-statistic is about 11 in the case of the contemporaneous term, suggesting that this instrumental variable is not a weak instrument. The second-stage estimate is positive but statistically insignificant. Compared with our baseline results from our main instrument, the magnitudes of the coefficient estimates are slightly lower (0.004 vs. 0.007). The two other instruments that rely on the lag and lead of the growth of US military aid assistance show signs of weakness, with low Kleibergen-Paap F-statistics, suggesting caution for the interpretation of the estimates. Nonetheless, we note that the results obtained from these alternative instruments remain qualitatively identical to our baseline estimates.

6.4.4 Accounting for the zeroes in cocaine seizure

Many municipalities did not have any counterinsurgency interventions during the period of our analysis, leading to a large number of zeroes in the antinarcotics operations variable, with the remaining, nonzero observations having a skewed distribution. This raises the possibility that there might be two distinct mechanisms at play: one that determines whether a municipality hosts any counterinsurgency interventions, and conditional on this, the frequency of the counterinsurgency operations.

To account for both endogeneity and this two-stage process, we adopt a control function approach for nonlinear instrumental variable estimation (Wooldridge, 2014), where we model the untransformed endogenous variable as a two-part model (two-step residual inclusion model, 2SRI). We first model the binary variable of nonzero cocaine seizure in a given municipality-year, using a probit model, and store the predictions. Secondly, we estimate the conditional expectation function among the nonzero observations, and store the prediction for each observation (including the zeros). Thirdly, we estimate the conditional mean for each municipality-year by multiplying the previous two predictions, and generate a residual by subtracting it from the observed value of the coca seizure variable. We use these residuals in the same second-stage model that is used in our baseline 2SLS specifications (see Appendix C.1 for further details). Table A1 presents the results with the 2SRI model, with the second-stage estimates in panel A and the first-stage residuals in panel B. The results confirm the strength of the interacted instrument between the probability of cocaine seizure and the growth rate of US military aid assistance in predicting antinarcotics operations. In panel A, the coefficient estimate on antinarcotics operations (cocaine seizure) is small, negative and statistically insignificant. This result, which is qualitatively similar to our baseline estimates, confirms the robustness of our finding when addressing the skewness of the endogenous variable.

6.4.5 Municipalities with weak state presence

Under Plan Colombia, the US strategy is clearly stated as "to gain control of drug trafficking [...], the rebuilding of institutions, and extending state presence where it was weak or nonexistent". One possibility for the exclusion restriction to be violated is if the change in the growth rate of US military aid assistance indirectly affects municipality health transfers through its effect on the Colombian national health budget. Although yearly changes in public healthcare spending should be absorbed by the department-time fixed effects, the Colombian government may decide to systematically change its health transfers for some specific municipalities, such as those with weak state presence. In this case, the growth rate of US military aid assistance would affect both antinarcotics operations and the growth rate of municipality health transfers. We account for this possibility by excluding municipalities from the departments where the state had little presence during the 2002-2015 period (Putumayo, Caqueta, Guaviare and Meta), as we could expect fewer public resources to be allocated to these departments by the central government. Table A2 in the online appendix presents the FE and 2SLS estimates from our baseline specifications with the exclusion of the departments cited above (comprising 26 municipalities). The results are qualitatively identical to our baseline results: the coefficients estimates on cocaine seizures are lower with both the FE and 2SLS models when we exclude these municipalities, but remain statistically insignificant.

7 Treatment effect heterogeneity

First, we explore the possibility that health transfers are allocated differently to municipalities at the upper tail of the distribution of antinarcotics interventions. For example, the central government could identify municipalities where the likelihood of rampant drug trafficking and violence by illegal armed groups is high and which would be perceived to require sustained transfers of resources for health, security and other public functions. To address those challenges, the government could reallocate public resources accordingly, including health transfers. To test this hypothesis, we split our sample into ten deciles over the 2002-2015 period and estimate the following regression

$$\Delta ln(SGP_{mdt}) = \sum_{i=1}^{i=10} \beta_i Antinarcotics_{mdt} + \mathbf{X}'_{mdt}\gamma + \alpha_m + \lambda_{dt} + \epsilon_{mdt} \tag{5}$$

where i indexes the deciles in the distribution of the probability of antinarcotics operations, the rest of the notation being similar to equation (1).

Figure 5 plots the coefficients on the antinarcotics operations variable for each decile (β_{1i}), along with their 95 % confidence intervals. The figure documents a similar effect of antinarcotics operations on the growth rate of health transfers across deciles where each coefficient is insignificant and tightly centred around zero.

Next, we test for the possibility of heterogeneous effects of antinarcotics operations according to municipalities' characteristics. We construct a series of municipality level indicators I_{mdt} for being above the sample median of the variable of interest. These characteristics, detailed below, whose influence is captured by in the municipality fixed effects in our baseline models, might provide additional information to better understand the mechanisms at play. In each regression, we instrument the interaction between the indicator and antinarcotics interventions with a triple interaction between the probability of cocaine seizure, the growth rate of US military aid assistance and the indicator of interest, and we add a separate interaction term between US military aid assistance and the indicator.

Table 9 examines the results, where column 1 reproduces our baseline estimates from the 2SLS estimation as a benchmark.

We start by investigating the possibility that increased transfers are systematically unreported due to higher corruption in municipalities where drug enforcement operations are conducted, which might lead to lower estimated treatment effects for the municipalities with higher levels of corruption. Columns 2-3 in table 9 explore this opportunistic behaviour hypothesis. We use data collected by Martínez (2019) from the Office of the Inspector General of Colombia on the prosecutions of mayors and local municipal officials for suspected involvement in corruption, to construct an indicator variable equal to one for each year when a prosecution is being conducted in a municipality. The interaction term with prosecution captures the differential effect of antinarcotics operations in municipalities with suspected cases of corruption, with respect to municipalities with no such cases. The estimated coefficient of interest is positive but statistically insignificant.

Columns (4-7) report the estimates of interactions terms with the following financial characteristics: debt, dependence on government transfers, the municipalities own resources and saving capacity. We find some evidence that any effects of antinarcotics interventions on health transfers, which should be quantitatively small according to the baseline estimations, operate through municipality dependence on government transfers, a measure defined as the share of central government transfers on the municipality's total public spending. Note also that the Kleibergen-Paap F-statistics in the first-stages are all relatively low (around 5). The estimates might therefore suffer from weak instruments.

8 Discussion and Conclusion

Protracted internal conflicts – long-running chronic confrontations – have become common in recent decades, affecting low- and middle-income countries disproportionally. The consequences for health and development have been devastating: beyond the immediate effects of protracted violence through casualties, health and welfare may be affected in the longer term by destruction of economic assets, damage or lack of access to public healthcare and other infrastructure, and population displacements (Justino, 2006). Unless effective remedial actions are put in place by the public sector to protect the health of civilian populations during periods of sustained confrontations, protracted violence is likely to aggravate ill health, poverty and inequalities through (among others) unmet healthcare needs, reduced ability to work, depletion of assets and savings to cope with health losses, and financially catastrophic healthcare payments (Kruk et al., 2010). If the public sector focuses solely on its military actions against local insurgent groups, without implementing effective public healthcare responses and safety nets that enhance the protection of health and welfare of civilians in the areas affected, the potentially larger scale of violence may further hamper public service provision and/or cause negative welfare spillovers to other localities through, for instance, internally displaced populations fleeing from violence. Therefore, understanding the dynamics of public healthcare responses amid conflict violence is critical to guide public policies that can promote the health and economic recovery of conflict-affected areas and their populations.

This paper offers novel evidence about local public financing responses during periods of increased violence stemming from government military actions against insurgent groups. We focus on the case of public healthcare financing patterns during the protracted conflict in Colombia, examining data about government-sponsored counterinsurgency interventions aimed at disrupting the funding sources of insurgent groups, namely antinarcotics operations at the municipality level. We analyse our data through panel estimations and instrumental variables, with consistent results obtained across multiple econometric specifications and robustness checks undertaken.

The first main message from our analyses is that there is no evidence of systematic – or otherwise important – changes in local public healthcare financing as a response (or accompanying) counterinsurgency operations implemented in Colombian municipalities. We find that antinarcotics operations in a given municipality do not causally affect healthcare transfers to the same municipality, either contemporaneously or in a lagged fashion. The absence of a response in terms of government health transfers may indicate that the allocation of public resources simply follows a fixed allocation rule which may in turn fail to address changes in local population health following changes in the levels of local violence. The findings also indicate that the Colombian central government has not been reducing public healthcare transfers to particular municipalities as a way of eroding local support for the presence of illegal armed groups.

Although our main conclusion above emerges from a richer dataset at the subnational level, it is consistent with the finding of the cross-country study by Gupta et al. (2004) of increased government spending during armed conflicts but which is directed primarily to the defense sector and financed through higher public deficit, whilst spending on social sectors like health and education remains generally unchanged. As Gupta et al. (2004) and Blattman and Miguel (2010) have suggested, increased levels of conflict-related violence are likely to have negative impacts on local economic growth and public revenues, therefore reducing the fiscal space available for expanding health financing when the government's priority is shifted towards defense spending. In the context of our study, this would indicate that the substantial additional resources obtained under Plan Colombia have been dedicated to enhance the state's capacity to undertake counterinsurgency operations (i.e. primarily its defense budget), while not releasing resources for other public areas of spending and, more specifically, not addressing the issue of enabling a health safety net for the civilian populations affected by the increased violence arising directly from such operations.

The above is a particularly relevant result in light of the second main finding from our analyses: counterinsurgency operations carried out in a municipality in a given year tend to raise general (non-state) levels of violence in the following period. This is consistent with the possibility of non-state illegal groups reacting to a fundamental threat to their existence, namely the disruption in local drug trafficking activities as a key funding source (which was patent and widespread in Colombia in the case of the largest illegal armed groups) (Mejía and P. Restrepo, 2016). While such reaction, with its resulting raised levels of local violence, is likely to be a response against the government and its attempt to restore the social contract between the state and the local community, it may also be a response against rival illegal groups' attempts to seize these localities after counterinsurgency operations have weakened the incumbent group (Dell, 2015) – or indeed a mixture of these possibilities.

In any event, the findings in our paper highlight the role of counterinsurgency operations as a channel that may have contributed in Colombia to the widely documented negative consequences of sustained conflict violence for the health of local populations (Levy and Sidel, 2016; Bendavid et al., 2021). To mitigate any further deleterious health effects stemming from counterinsurgency efforts, a policy implication of our study is that such efforts must be accompanied by measures to support – and in fact, strengthen – public healthcare financing and provision for the affected local communities. The benefits of such a policy strategy are likely to be two-fold: in addition to protecting people's health during and in the immediate aftermath of counterinsurgency-related violence, enhanced public healthcare financing and provision may contribute to strengthen the state's legitimacy locally and reduce illegal armed group activities in the future (Berman et al., 2011).

As in any empirical study, our analyses are not free from limitations. We take extra care in this study to address endogeneity concerns around the relationship between health transfers by the government, and the timing and placement of counterinsurgency operations. This includes the adoption of instrumental variable approaches and a battery of specification and robustness tests, which reinforce our baseline conclusions. Yet data limitations preclude further testing that could be important to offer further reassurance about causal inference in our setting. In particular, we are unable to completely rule out the existence of hidden political arrangements governing, simultaneously, both the growth rate of health transfers to a given municipality and the selection of such municipality to receive an antinarcotics operation. More detailed data about financing decisions pertaining to healthcare and other social sectors at the national and subnational levels, under the different combinations of incumbent political parties (hopefully over an even longer period time), as well as documentary evidence, would have allowed testing the hypothesis of hidden political arrangements in our context.

Contexts of protracted conflict-related violence require carefully designed public policies to protect local populations against potentially devastating consequences in terms of health and welfare. For that aim, evidence-based guidance is crucial. Taken together, the results from our case study in Colombia provide strong evidence that government actions against insurgent groups must shift from nearly exclusive attention to military aspects, towards strategies that also encompass accompanying measures to strengthen the financing and capacity of local health systems. This strategy shift is bound to generate dividends not just via protecting the health of vulnerable populations in the short-run (important as this is), but also via subsequent general violence reduction and enhanced state legitimacy among local communities in the long-run.

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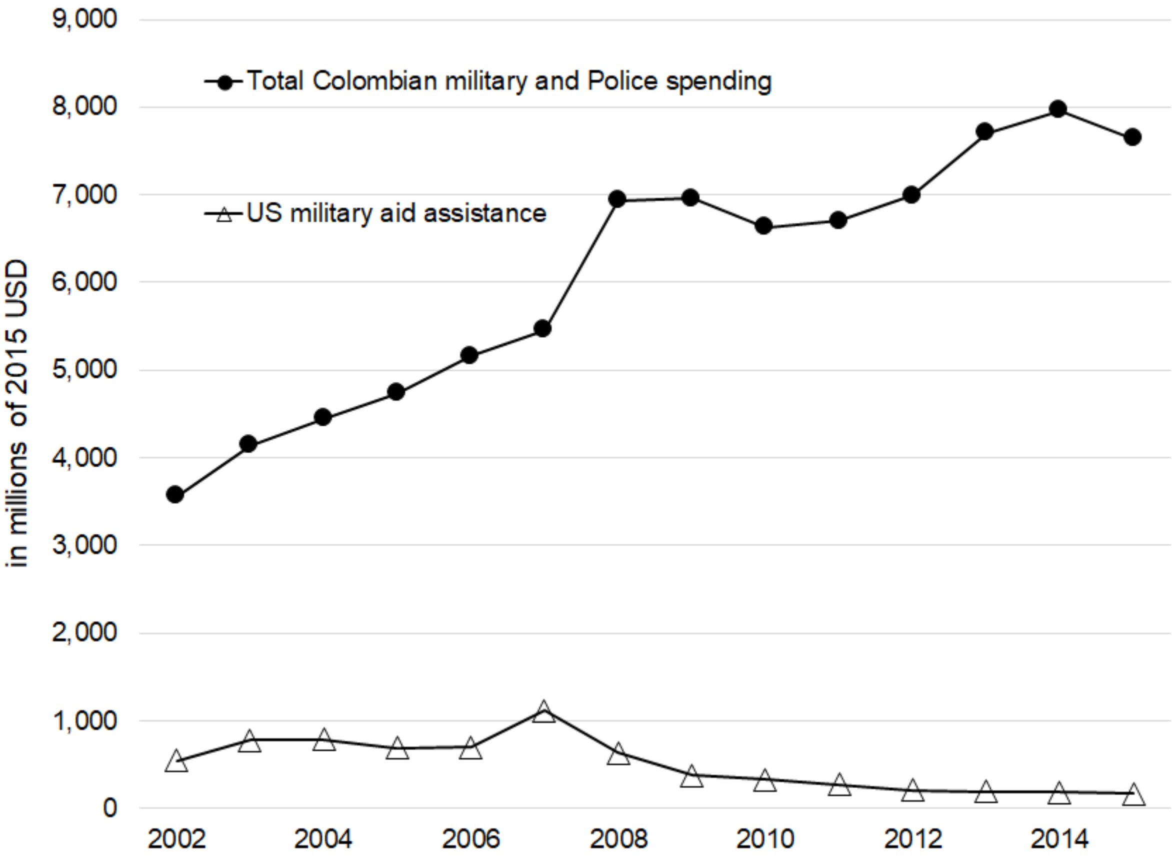
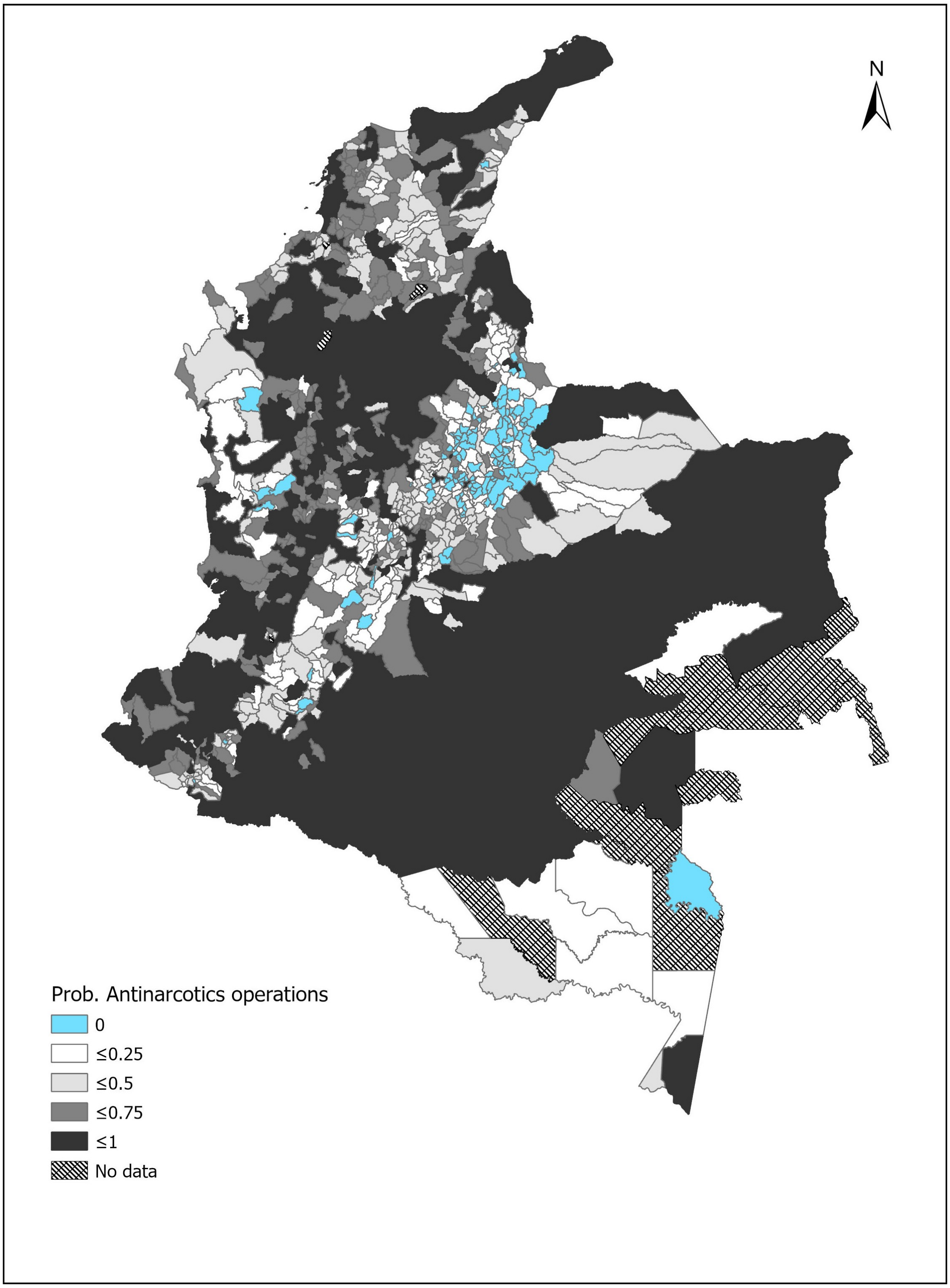
Figure 1: Evolution of the Colombian national military budget and US military aid assistance



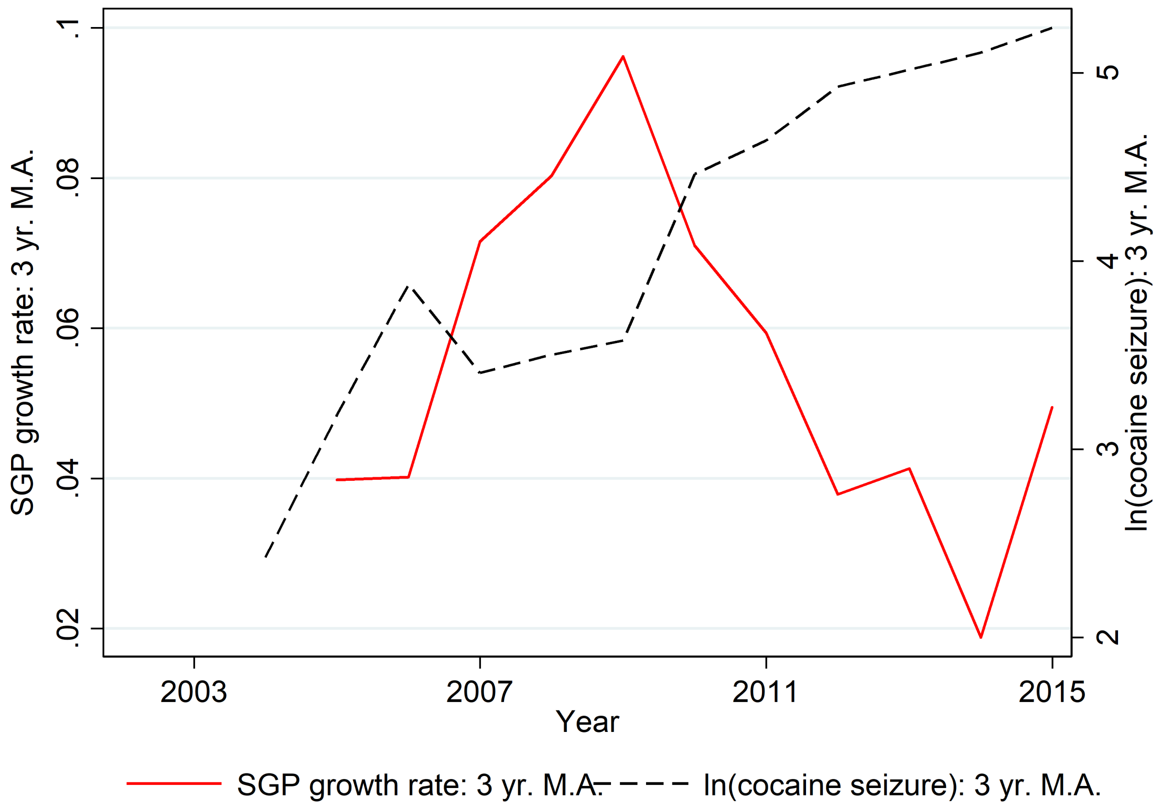
Notes: The graph plots the evolution of US military aid assistance (white triangles) and the total Colombian military and Police spending (black dots) in millions of 2015 U.S. Dollars (USD) between 2002 and 2015. US military aid assistance corresponds to U.S. funding for reducing illicit Narcotics and Improving Security, and was obtained from Security Assistance Monitor and supplemented with reports from the Congressional Research Service on Colombia. The U.S. foreign security assistance was mostly devoted to military financing, equipment, training and counter-drug assistance. Data on Colombian Military and Police spending was obtained from the Ministry of Defense.

Figure 2: Distribution of the probability of antinarcotics interventions



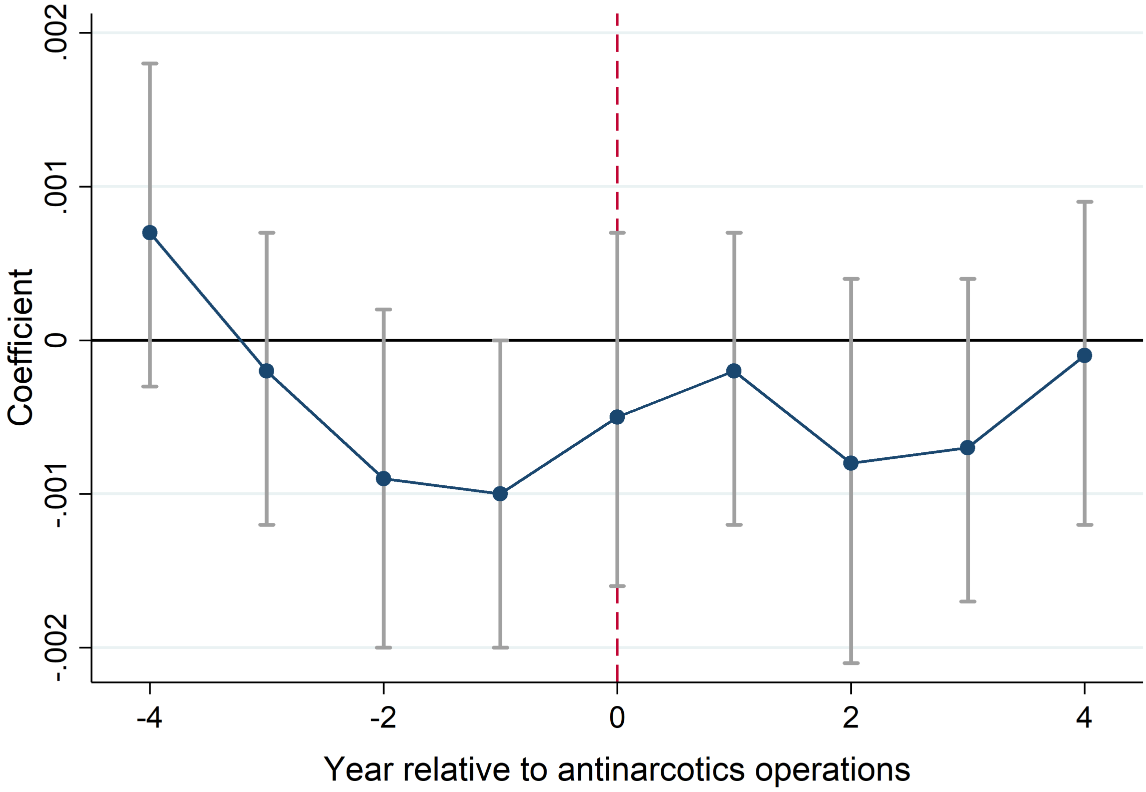
Notes: The map depicts the geographic distribution of the probability of antinarcotics interventions, $ProbaCoca_{mdt}$. Blue areas indicate to municipalities without any interventions over the 2002-2015 period. We classify the distribution of the probability of interventions by quartile, using white and grey for the first two quartiles of the distribution and dark grey and black for the third and fourth quartiles. Municipalities with no data appear in dashed black areas, and mostly correspond to remote areas of the Amazon jungle in the South of the country.

Figure 3: Public healthcare spending and cocaine seizure



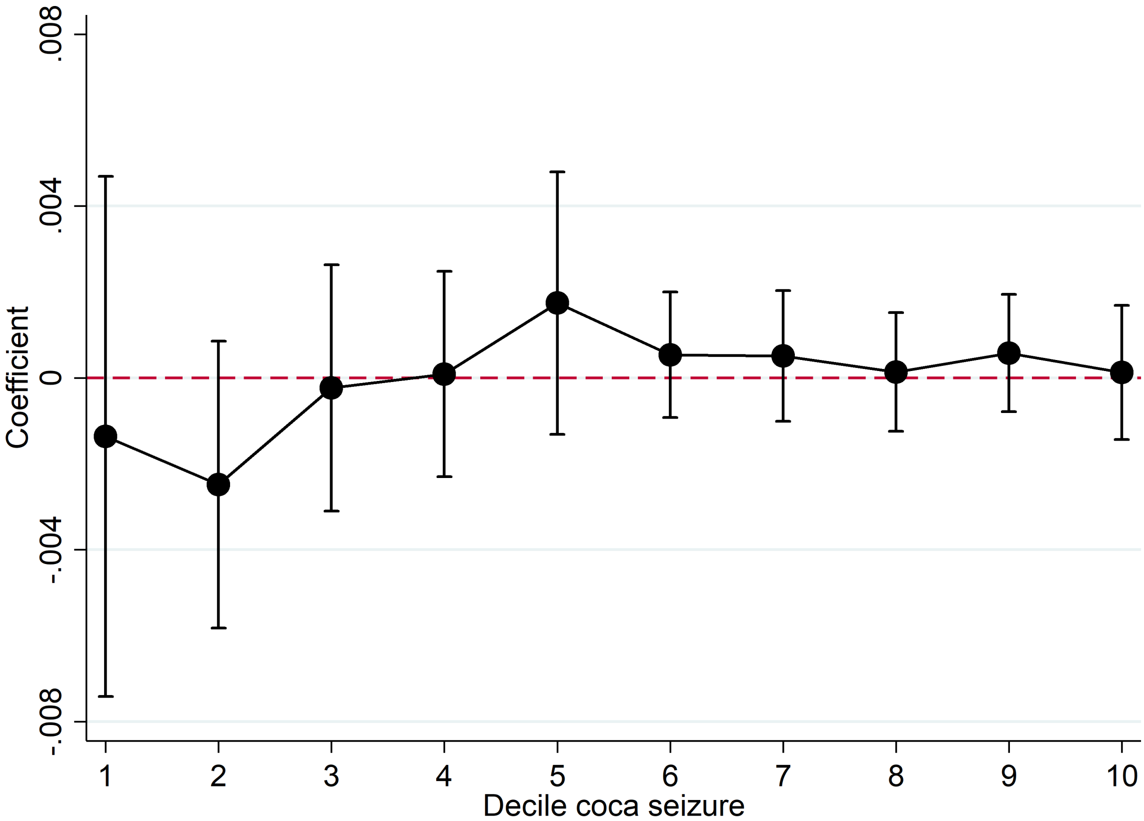
Notes: The red line indicates the 3-year moving average of the growth rate of public healthcare spending (SGP). The black dashed line indicates the logarithm of the quantity of cocaine paste and cocaine hydrochloride seizure in grams. The latter was collected from the Anti-Narcotics department of the Colombian National Police.

Figure 4: Dynamic effects of counterinsurgency



Notes: The graph plots the coefficient estimates from the baseline FE specification (1) augmented with four lags and four leads of the variable antinarcotics operations. The blue dots are the point estimates on the antinarcotics operations variables and the grey lines indicate 95 % confidence intervals. Regressions include all baseline controls and robust standard errors adjusted for clustering at the municipality and department-year level.

Figure 5: Effect of counterinsurgency on health transfers by cocaine seizure decile



Notes: The graph plots the point estimates of antinarcotics operations from the FE estimation (equation 1) where antinarcotics operations is fully interacted with the deciles of the distribution of cocaine seizure. All regression include all baseline controls and standard errors are adjusted for clustering at the municipality and department-year level.

Table 1: First-stage: validity of the main instrument

	(1) Municipality FE	(2) Controls+ FE	(3) Controls+ Depart-Year FE	(4) Excluding weak state	(5) Uribe presidency	(6) lagged instrument	(7) Controls+ Depart-Year FE
Dependent variable:	Antinarcotics operations						
Prob. cocaine seizure × Growth(US Aid)	-5.7588***	-5.6006***	-4.5976***	-4.5499***	-4.9974***	-5.0635***	
	(0.4792)	(0.4966)	(0.8124)	(0.8338)	(0.8994)	(1.0826)	
Prob. cocaine seizure × Growth(US ODA)							-0.1626
							(0.2455)
F-statistic	144.40	127.18	32.03	29.78	30.87	21.88	0.44
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	No	No	No
Department-year FE	No	No	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8706	8706	8706	8275	3939	8298	13169
Municipalities	1065	1065	1065	1007	1020	1062	1098

Notes: The table presents the first-stage results from equation (3) where the dependent variable is antinarcotics operations capture by the IHS transformation of the cocaine seizure variable. The main explanatory variable is the interaction between the probability of cocaine seizure ($ProbaCoca_{mdt}$) and the growth of US military aid assistance (columns 1-6). Column 7 presents a falsification test with the instrument based on the interaction between the probability of cocaine seizure and the growth of Official Development Assistance (ODA) (total net disbursements) from the US to Colombia and which was collected from the database of the OCED Creditor Reporting System. The standard errors are clustered at the municipality level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 2: Summary statistics

	Mean	SD	Min	Max	Obs.
Panel A. Main outcomes					
Growth rate(SGP - health)	0.03	0.15	-3.68	3.60	14,274
Growth rate(SGP - Total)	0.07	0.15	-1.02	1.59	14,274
Panel B. Controls					
asinh(Cocaine seizure)	4.39	5.13	0.00	18.36	15,372
ln(Cocaine seizure+1)	4.05	4.84	0.00	17.66	15,372
ln(Share of Subsidised regime pop.)	0.65	0.23	0.00	1.57	15,372
ln(Population)	9.57	1.10	6.70	15.88	15,372
ln(Municipality GDP)	11.71	1.29	7.33	19.04	14,266
Distance to capital of Department in km	78.92	56.07	0.00	376.12	15,372
Nb. health facilities	1.46	2.55	1.00	63.00	12,474
Oil and Mineral resources (dummy)	0.11	0.31	0.00	1.00	15,372
Index of rurality	0.57	0.24	0.00	0.98	15,372
ln(homicide)	1.66	1.74	0.00	8.74	15,372
ln(war acts+1)	0.34	0.68	0.00	4.76	15,372
Panel C. Instruments					
Probability coca seizure	0.51	0.32	0.00	1.00	15,372
Growth rate US Aid	-0.09	0.28	-0.56	0.47	14,274
Margin outcome right-wing mayors	0.06	0.20	-0.85	1.00	11,056
Governor right party (dummy)	0.23	0.42	0.00	1.00	15,372

Notes: All statistics are reported at the municipality level. Panel A presents the dependent variables that are used in the analysis, panel B presents the baseline controls and panel C shows the statistics for the variables that are used in the construction of the instrument variables. All variable definitions and data sources are provided in section A of the online appendix.

Table 3: The effect of antinarcotics interventions on public health transfers

Panel A: Panel data estimation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent variable: Growth rate of health transfers									
Model:	FE				2SLS					
asinh(Coca seizure)	0.0014*** (0.0005)		0.0008 (0.0005)		0.0087 (0.0072)		0.0102 (0.0074)		-0.0067 (0.0090)	
ln(Coca seizure+1)		0.0015*** (0.0006)		0.0009* (0.0005)		0.0095 (0.0079)		0.0111 (0.0081)		-0.0074 (0.0099)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No
Department-year FE	No	No	Yes	Yes	No	No	No	No	Yes	Yes
Population share under subsidised regime	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Colombian president × Avg. probability coca seizure	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Right Governor × Avg. probability coca seizure	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Municipality characteristics × year FE	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
ln(Municipality GDP)	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
ln(Population)	No	No	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Observations	8703	8703	8703	8703	8703	8703	8703	8703	8703	8703
Municipalities	1062	1062	1062	1062	1062	1062	1062	1062	1062	1062

Panel B: First-stage of the corresponding 2SLS panel regressions

	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable:	asinh (Coca seizure)	ln (Coca seizure+1)	asinh (Coca seizure)	ln (Coca seizure+1)	asinh (Coca seizure)	ln (Coca seizure+1)
Prob. cocaine seizure × Growth(US Aid)	-5.7588*** (0.9471)	-5.2895*** (0.8715)	-5.6006*** (0.7910)	-5.1237*** (0.7227)	-4.5976*** (0.9216)	-4.1782*** (0.8567)
Kleibergen-Paap F-statistic	36.97	36.84	50.13	50.26	24.89	23.78
Controls as in panel A	Yes	Yes	Yes	Yes	Yes	Yes

Notes: FE estimates are obtained from equation (1) and reported in columns 1-4, while 2SLS estimates are shown in columns 5-10. Additional controls include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, which are all interacted with year dummies, as well as the logarithm of population and a rurality index. Cocaine seizure is instrumented by the interaction of the probability of cocaine seizure with the growth of US military aid assistance. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 4: The effect of antinarcotics interventions on other public transfers

Panel A: Panel data estimation

	(1)	(2)	(3)
	Dependent variable: Growth rate of total public transfers		
Model:	2SLS		
asinh(Coca seizure)	0.0022 (0.0078)		
asinh(Coca seizure)(t-1)		0.0003 (0.0083)	
asinh(Coca seizure)(t+1)			0.0100 (0.0179)
Municipality FE	Yes	Yes	Yes
Department-year FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Observations	12071	10974	10974
Municipalities	1098	1098	1098

Panel B: First-stage of the corresponding 2SLS panel regressions

	(1)	(2)	(3)
Dependent variable:	asinh(Coca seizure)	asinh(Coca seizure) (t-1)	asinh(Coca seizure) (t+1)
Prob. cocaine seizure × Growth(US Aid)	-5.2966*** (0.7817)		
Prob. cocaine seizure × Growth(US Aid)(t-1)		-4.0772*** (0.9991)	
Prob. cocaine seizure × Growth(US Aid)(t+1)			-3.1898*** (0.8367)
Kleibergen-Paap F-statistic	45.91	16.65	14.53
Controls as in panel A	Yes	Yes	Yes

Notes: All results are 2SLS estimations in panel A and first-stage estimates in panel B. The dependent variable is the total public transfers to municipality net of health transfers (comprise transfers for education, drinking water and sanitation, and general purposes). Columns (1) and (2) report the coefficients estimates from the regression of antinarcotics interventions on the growth rate of the share of municipality in the country's Gross Domestic Product (GDP) and columns (3) and (4) report the growth rate of municipality public spending. The growth rate is expressed as the natural log-difference. Baseline controls are those presented in table 3. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 5: The effect of antinarcotics interventions on local violence

Panel A: Panel data estimation				
	(1)	(2)	(3)	(4)
Dependent variable:	Homicides		Acts of war	
Model:	2SLS			
asinh(Coca seizure)	-0.0758		-0.0629**	
	(0.0518)		(0.0281)	
asinh(Coca seizure)(t-1)		-0.1375**		0.0530**
		(0.0580)		(0.0239)
Municipality FE	Yes	Yes	Yes	Yes
Department-year FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Observations	14274	13176	14274	13176
Municipalities	1098	1098	1098	1098

Panel B: First-stage of the corresponding 2SLS panel regressions				
	(1)	(2)	(3)	(4)
Dependent variable:	asinh(Coca seizure)	asinh(Coca seizure) (t-1)	asinh(Coca seizure)	asinh(Coca seizure)(t-1)
Prob. cocaine seizure × Growth(US Aid)	-3.2058***		-3.2058***	
	(0.6042)		(0.6042)	
Prob. cocaine seizure × Growth(US Aid)(t-1)		-3.1658***		-3.1658***
		(0.5841)		(0.5841)
Kleibergen-Paap F-statistic	28.15	29.37	28.15	29.37
Controls as in panel A	Yes	Yes	Yes	Yes

Notes: All results are 2SLS estimations in panel A and first-stage estimates in panel B. The dependent variable is the total public transfers to municipality net of health transfers (comprise transfers for education, drinking water and sanitation, and general purposes). Columns (1) and (2) report the coefficients estimates from the regression of antinarcotics interventions on the growth rate of the share of municipality in the country's Gross Domestic Product (GDP) and columns (3) and (4) report the growth rate of municipality public spending. The growth rate is expressed as the natural log-difference. Baseline controls are those presented in table 3. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 6: The effect of antinarcotics interventions controlling for lagged transfers

Panel A: Panel data estimation					
	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Growth rate of SGP				
Model:	2SLS				
asinh(Cocaine seizure)	-0.0067	-0.0033	-0.0105	-0.0026	0.0008
	(0.0090)	(0.0036)	(0.0116)	(0.0037)	(0.0124)
Growth SGP(t-1)		-0.3887***	-0.4811***	-0.4502***	-0.6269***
		(0.0639)	(0.0705)	(0.0622)	(0.0670)
Growth SGP(t-2)				-0.1463**	-0.4030***
				(0.0627)	(0.0644)
Growth SGP(t-3)				0.0152	-0.1827***
				(0.0285)	(0.0365)
Municipality FE	Yes	No	Yes	No	Yes
Department-year FE	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Observations	8703	8298	8298	7018	7018
Municipalities	1062		1062		1062

Panel B: First-stage of the corresponding 2SLS panel regressions					
			(4)		(5)
Dependent variable:			asinh(Cocaine seizure)		asinh(Cocaine seizure)
Prob. cocaine seizure × Growth(US Aid)	-4.5976***	-12.9796***	-4.1942***	-12.5485***	-4.0149***
	(0.9216)	(2.0363)	(0.9609)	(1.9503)	(0.9261)
Kleibergen-Paap F-statistic	24.89	40.63	19.05	41.4	18.79
Controls as in panel A	Yes	Yes	Yes	Yes	Yes

Notes: Each point estimate is obtained from the 2SLS estimation of equation (1) where cocaine seizure is instrumented by the interaction of the probability of cocaine seizure with the growth of US military aid assistance. Baseline controls are those indicated in table 3. Additional controls include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, which are all interacted with year dummies, as well as the logarithm of population and a rurality index. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 7: The effect of lead and lagged antinarcotics interventions on public health transfers

Panel A: Panel data estimation				
	(1)	(2)	(3)	(4)
	Dependent variable: Growth rate of SGP			
Model:	FE		2SLS	
asinh(Cocaine seizure) (t-1)	-0.0006		-0.0021	
	(0.0004)		(0.0045)	
asinh(Cocaine seizure) (t+1)		-0.0008*		0.0113**
		(0.0004)		(0.0056)
Municipality FE	Yes	Yes	Yes	Yes
Department-year FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Observations	10975	10974	10975	10974
Municipalities	1098	1098	1098	1098

Panel B: First-stage of the corresponding 2SLS panel regressions		
	(3)	(4)
Dependent variable:	asinh(Coca seizure) (t-1)	asinh(Coca seizure) (t+1)
Prob. cocaine seizure × Growth(US Aid) (t-1)	-9.1885***	
	(1.0730)	
Prob. cocaine seizure × Growth(US Aid) (t+1)		-4.2440***
		(0.8512)
Kleibergen-Paap F-statistic	73.34	24.86
Controls as in panel A	Yes	Yes

Notes: FE estimates are obtained from equation (1) and reported in columns 1-2, while 2SLS estimates are shown in columns 3-4. Baseline controls are those indicated in table 3. Additional controls include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, which are all interacted with year dummies, as well as the logarithm of population and a rurality index. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 8: The effect of antinarcotics interventions on public health transfers: alternative instruments

Panel A: Panel data estimation				
	(1)	(2)	(3)	(4)
	Dependent variable: Growth rate of SGP			
Model:	2SLS			
asinh(Coca seizure)	0.0241	0.0037		
	(0.0197)	(0.0077)		
asinh(Coca seizure)(t-1)			-0.0202	
			(0.0144)	
asinh(Coca seizure)(t+1)				0.0071
				(0.0125)
Municipality FE	Yes	Yes	Yes	Yes
Department-year FE	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Observations	10975	8703	8298	8085
Municipalities	1098	1062	1062	1062

Panel B: First-stage of the corresponding 2SLS panel regressions				
	(1)	(2)	(3)	(4)
Dependent variable:	asinh(Coca seizure)	asinh(Coca seizure)	asinh(Coca seizure) (t-1)	asinh(Coca seizure) (t+1)
Prob. cocaine seizure × Growth(US Aid)(t-1)	-1.7000**			
	(0.7279)			
Right Margin × Growth(US Aid)		2.1867***		
		(0.6647)		
Right Margin × Growth(US Aid)(t-1)			2.0313**	
			(0.9300)	
Right Margin × Growth(US Aid)(t+1)				1.9550**
				(0.7783)
Kleibergen-Paap F-statistic	5.455	10.82	4.771	6.31
Controls as in panel A	Yes	Yes	Yes	Yes

Notes: All point estimates are obtained from the 2SLS estimation of equation (1) and presented in panel A, and first-stage estimates are shown in panel B. Baseline controls are those presented in table 3, and the additional controls are identical to those presented in the footnote of the same table. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 9: The heterogeneous effect of antinarcotics interventions on public health transfers

Panel A: Panel data estimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: Growth rate of SGP						
Model:	2SLS						
asinh(Coca seizure)	-0.0007	-0.0007	-0.0002	-0.0007	-0.0031	-0.0027	0.0008
	(0.0068)	(0.0068)	(0.0071)	(0.0074)	(0.0069)	(0.0085)	(0.0075)
asinh(Coca seizure)							
× Prosecution		0.0003					
		(0.0008)					
× Prosecution (lagged t-3)			-0.0045				
			(0.0038)				
× Debt				-0.0001			
				(0.0014)			
× Dependence government transfer					0.0043**		
					(0.0022)		
× Municipality own resources						0.0023	
						(0.0039)	
× Saving capacity							-0.0023
							(0.0016)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12072	12072	10974	11987	11987	11987	11987
Municipalities	1098	1098	1098	1097	1097	1097	1097
Panel B: First-stage of the corresponding 2SLS panel regressions							
Kleibergen-Paap F-statistic	46.33	15.59	17.21	15.55	17.67	10.82	13.80

Notes: All results are 2SLS estimations in panel A and first-stage estimates in panel B. Baseline controls are those presented in table 3. The instrument used is the interaction between the probability of coca seizure and the growth rate of US assistance (our main instrument has F-stat of approximately 4 which poses concerns of weak instrument). Dependence on government transfers is defined as the share of government transfers in total public spending. Municipality own resources refers to the capacity of a municipality to generate its own revenue out of total public spending. Saving capacity is equal to the difference between public revenue and spending out of total spending. Prosecution (lagged t-3) is a dummy variable equal to one in periods t-3, t-2 and t-1 if a suspected case of corruption occurs in year t. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Appendix for online publication

A Variable definitions and data source

Variable	Description
US military aid assistance	U.S. funding for reducing illicit Narcotics and Improving Security. The funding relates to the US financial support to Plan Colombia that started in 2000. The U.S. Assistance for Colombia by State Department Foreign Aid account comprises the following items: 1) International Narcotics Control and Law Enforcement (named Andean Counterdrug Program between 2000 and 2009); 2) Nonproliferation, Anti-Terrorism, Demining, and Related Programs; 3) Foreign Military Financing; 4) Combating Terrorism Fellowship Program and 5) Aviation Leadership Program. Source: Security Assistance Monitor (https://securityassistance.org/colombia) and reports for congress from Congressional Research Service on Colombia between 2002 and 2015 (www.crs.gov).
SGP	Municipality public transfers from the national government funds (*Sistema General de Participaciónes*). The transfers are divided into four subcomponents which are health, education, water and sanitation and other general purposes. The dependent variable in our baseline model is the health component of SGP transfers. Data collected from *Departamento Nacional de Planeación* (http://www.dnp.gov.co).
Antinarcotics interventions	Police and military interventions that are proxied by the total quantity of cocaine seized in a municipality and a year. The cocaine is either under the form of paste or transformed into cocaine hydrochloride. Data was collected from the National Police of the Ministry of Defence and the *Observatorio de Drogas de Colombia* (http://www.odc.gov.co/).

Variable	Description
Prosecution	Prosecutions of mayors and local municipal official on suspected involvement in corruption. We use data collected by Martínez (2019) from the Office of the Inspector General of Colombia.
Share of subsidised population	Share of the poorest and most vulnerable populations in a municipality who are covered under the subsidised regime. The beneficiaries are identified through a proxy-means test index (*Sistema de Identificación de Beneficiarios* , SISBEN) based on the socio-economic conditions of each household.
Acts of war	Acts that are carried out by the actors of the armed conflict with a defined military objective and using illicit means and weapons in combat (CINEP, 2008). Data collected from *Centro Nacional de Memoria Histórica* (CNMH).
Number of homicides	Number of homicide cases related to the armed conflict, and reported in the *Registro Único de Víctimas* (RUV).

B Instrument: Right-wing marginal mayoral outcome

B.1 Relationship with antinarcotics operations

The section explores the validity of our alternative instrument based on the interaction between the right margin outcome of mayoral elections with the growth rate of US military aid assistance.

Figure A2 documents the relationship between right-wing municipalities and the intensity of antinarcotics operations. The figure depicts the yearly average of the logarithm of cocaine seizure (in red) along with the yearly average share of right-wing municipalities that hosted antinarcotics operations (where cocaine seizure is higher than zero). The figure provides illustrative evidence that supports our hypothesis: after each mayoral election year, an increase in the share of right-wing municipalities is positively correlated with an increase average quantity of cocaine seizure. It therefore suggests a relationship between mayoral right-wing parties and the likelihood of antinarcotics operations.

We further anticipate that the frequency and intensity of military operations would be a function of the marginal outcome of the mayoral elections: a large right-wing victory would provide more legitimacy (through popular support) to support antinarcotics operations.

The excludability assumption might be violated if the government adjusts its transfers according to the winning party of mayoral elections. Since we cannot exclude the existence of potential hidden political arrangements, we explore this hypothesis in the following section.

B.2 Excludability of Right Margin instrument

This section explores the validity of the exclusion assumption on which we rely to conduct the IV strategy with the alternative instrument that interacts right marginal outcome in mayoral elections with the growth rate of US military aid assistance. The suitability of our instrument requires that mayoral outcomes do not directly affect government health transfers to municipalities. The latter are governed by an allocation-based formula which should reduces the possibility of discretionary changes with respect to political parties. To verify this assumption, we analyse in a difference-in-difference (DD) approach the effect of a change in mayoral political party of mayor on government health transfers. Specifically, we explore whether the national government modifies municipality health transfers close to mayoral elections in order to influence election outcomes. We compare municipalities that remain under right-wing mayoral political party after the municipal elections with municipalities that experienced a shift in political leadership. We estimate the following two-way fixed effects regression

$$\Delta log(SGP_{mdt}) = \beta(Post_{mt} \times Party_{mt}) + \gamma X_{mt} + \alpha_m + \lambda_{dt} + \epsilon_{mdt} \quad (6)$$

where $Post_{mt}$ is a dummy variable equal to one after the municipal election year and 0 otherwise; $Party_{mt}$ is an indicator denoting the mayoral political party in municipality mt belongs to the right-wing coalition. We include municipality and year fixed effects and cluster standard errors at the municipality level. The DD coefficient β measures how health transfers to municipalities that switch to non-right parties after the mayoral elections differ from transfers to municipalities that remained under the right coalition.

To test the common trend assumption between control and treated units and also detect anticipation effects, we perform an event study version of equation 6. We replace the post-election dummy variable with an indicator variable for each year relative to the election interacted with the right party indicator.

$$\Delta log(SGP_{mdt}) = \sum_{i=T-3}^{i=T+3} I(t=i) \times \beta_i Party_{mi} + \gamma X_{mt} + \alpha_m + \lambda_{dt} + \epsilon_{mdt} \tag{7}$$

The coefficients β_i capture the yearly effect of having a right-wing mayor on municipality health transfers. There are 4 election years in our 2002-2015 data sample (2003, 2007, 2011 and 2015) but we focus only on 2007 and 2011 ($T = \{2007, 2011\}$) for which we can fully cover the effect before and after the municipal elections. We study the dynamics within a 3-year window around the election year, excluding the election year. Our main assumption is that health transfers to municipalities with right-wing parties remain unchanged and after the elections.

Figure A3 provides visual evidence for the validity of our excludability assumption. The figure plots the coefficients β_i for the 2007 (panel A) and 2011 (panel B) mayoral elections, along with the 95% confidence intervals. For each election, the yearly estimated coefficients are statistically insignificant and suggest that the growth rate of health transfers to municipalities remain largely unaffected by political motives, both before and after election years. The results provide evidence that the government does not systematically reallocate the earmarked funds after each municipal election.

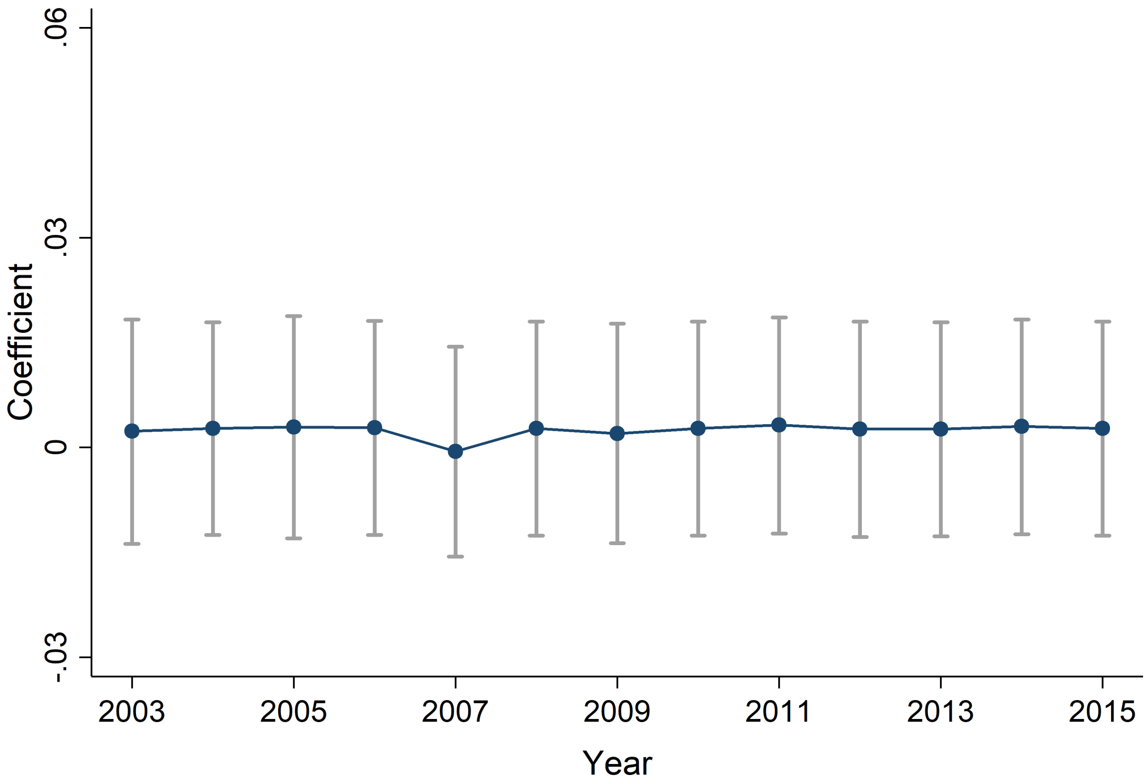
C Accounting for the zeroes: Two-stage Residual Inclusion approach

C.1 Variable construction and two-stage residual inclusion

Our main explanatory variable of interest is constructed in the following way. The raw, municipality level data of yearly coca paste seizures, is expressed in kg and recoded to zero if observations were smaller than one kg. We model the coca paste seizure variable as a count process in the instrumental variable analysis, and round the variable to the lower integer value. While in the raw data, 8,779 municipality-years had zero coca seizures, and 6,649 nonzero seizure, the modified variable contains 11,706 zero and 3,722 nonzero observations. The large number of zero observations in the endogenous variable needs to be accounted for in the instrument variable strategy we follow. We implement the method of two-stage residual inclusion, proposed by Terza et al. (2008). The approach we implement is described in Terza (2017), which we modify by exploring several specifications of the first stage. The first step of the approach entails modelling the conditional expectation of the endogenous coca seizure variable, as a function of the instrument and the remaining exogenous variables. We use the following modelling strategy for this. In a two-part model approach, we model the binary variable of coca seizure in a given municipality-year being nonzero, using a probit model, and store the predictions $Pr(X > 0|Z)$. We then estimate the conditional expectation function of X among the nonzero observations, $E(X|Z, X > 0)$, using a generalised linear model (GLM) with log link and gamma distribution, to account for the skewed distribution of coca seizure, and store the prediction for each observation (including the zeros). We then estimate $E(X|Z)$ by multiplying the previous two predictions, and generate a residual by subtracting it from the observed value of the coca seizure variable.

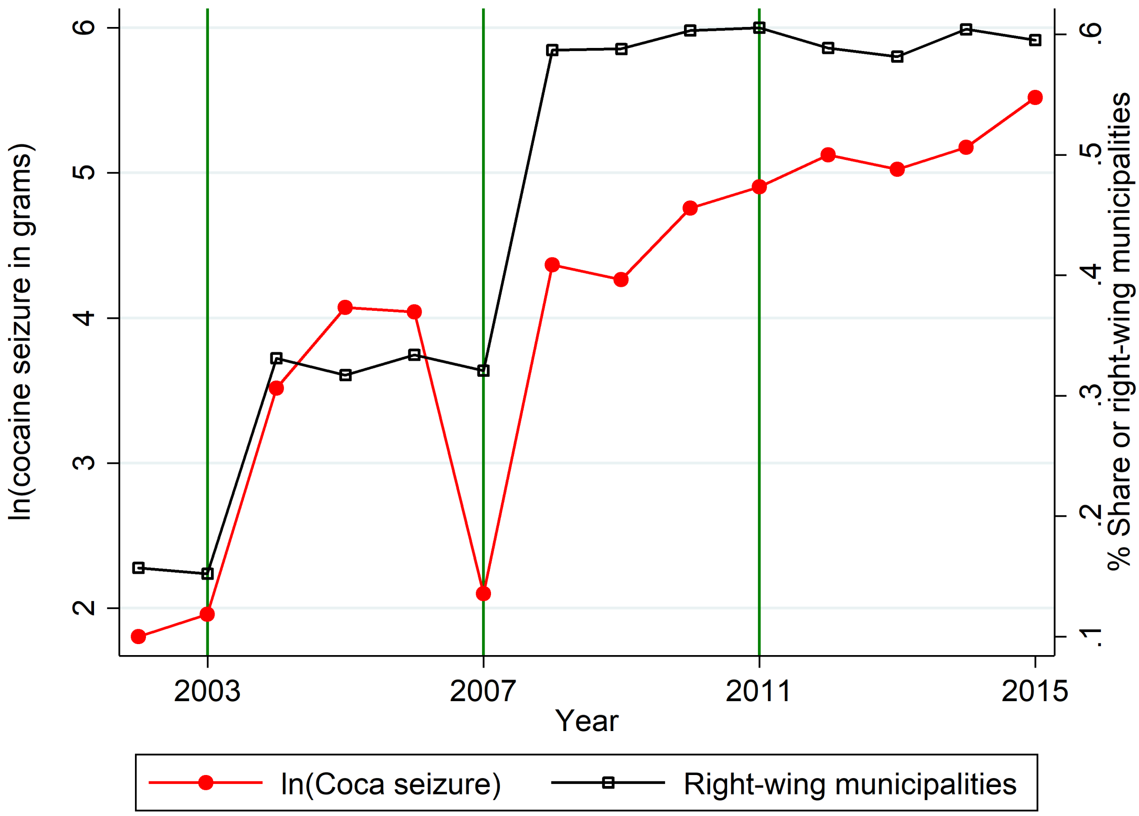
The second approach to estimate residuals is by implementing a GLM with gamma distribution and log link function among all the observations including zeroes, take a prediction from the fitted model, and calculate the residuals. Our third approach uses a zero-inflated negative binomial regression model, which handles the large number of zeros (inflation) by estimating a model for the probability of nonzeros. We generate predictions from the joint model, and estimate the residuals. In the second stage of the 2SRI approach, we include the residuals as an additional control. We implement FE linear regression models, where we include year dummies and municipality fixed effects. We bootstrap the entire procedure to account for uncertainty in the first stage estimation. We implement 1500 bootstrap replications, and account for panel structure of the data when drawing bootstrap samples. The method can deliver consistent estimates under the assumption that each instrument and the errors terms ν_{mt} and ϵ_{mdt} from equations 1 and 3 are independent, and the instrument is uncorrelated with ν_{mt} (Wooldridge, 2014).

Figure A1: Heterogeneity effect of counterinsurgency: yearly interactions



Notes: The graph plots the coefficient estimates on the interaction between antinarcotics operations and year dummies (in blue dots) obtained from our baseline 2SLS estimation. The grey lines indicate 95 % confidence intervals. Regressions include all baseline controls and robust standard errors adjusted for clustering at the municipality and department-year level.

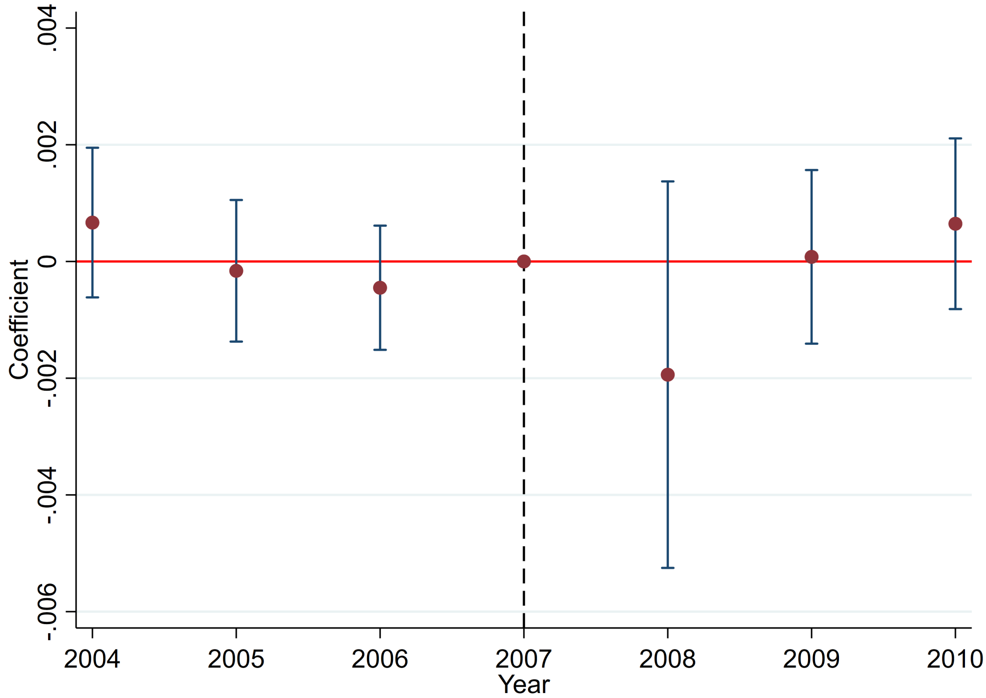
Figure A2: Right-wing municipalities and antinarcotics operations



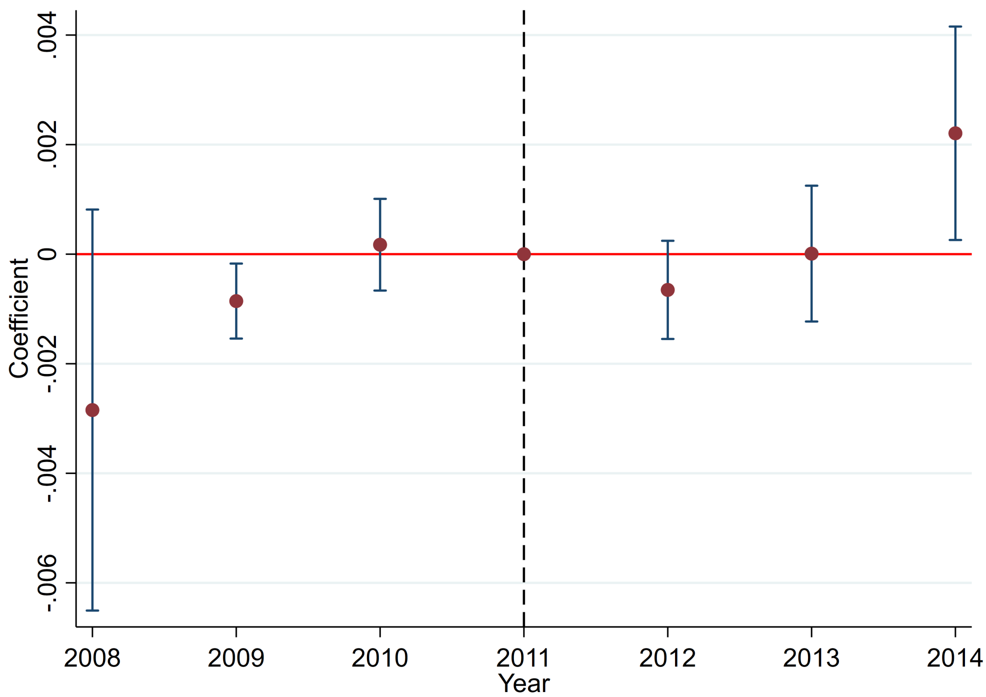
Notes: The graph plots the yearly average quantity (in logarithm) of cocaine seizure in grams (in red) and the yearly average share of right-wing municipalities that hosted antinarcotics operations (where cocaine seizure is higher than zero). Mayoral elections in 2003, 2007 and 2011 are indicated by vertical green lines. Since the mayoral political party can only change after a mayoral election, an increase (decrease) in the yearly average percentage of right-wing municipalities simply reflects the increase (decrease) in the share of municipalities that hosted antinarcotics operations.

Figure A3: Event studies: health transfers and mayoral elections

(A) 2007 mayoral elections



(B) 2011 mayoral elections



Notes: The graph plots event study coefficients of equation (7) with 95 % confidence intervals. Panels (A) and (B) present the β_i coefficients on the interaction of yearly indicator and right party dummy for the 3 years before and after the 2007 and 2011 mayoral election respectively (vertical dashed line). Standard errors adjusted for clustering at the municipality and department-year level.

Table A1: The effect of antinarcotics interventions on public health transfers: 2SRI model

Panel A: 2nd-stage two-part 2SRI model	
Dependent variable:	Growth rate of SGP
Cocaine seizure (in tons)	-0.0011
	(0.0031)
Baseline controls	Yes
Year FE	Yes
Department-year FE	No
Observations	15372
Municipalities	1098

Panel B: First-stage residuals		
	1st stage probit	1st stage GLM
	(1)	(2)
Dependent variable:	Cocaine seizure	Cocaine seizure
Prob. cocaine seizure × Growth(US Aid)	-7.4830***	-6.3437***
	(0.2824)	(1.1619)
Controls as in panel A	Yes	Yes

Notes: The table presents the results from the 2SRI model in panel A and the first stage residuals in panel B. The cocaine seizure variable is taken in level and expressed in tons. Baseline controls are those presented in table 3, and the additional controls include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, which are all interacted with year dummies, as well as the logarithm of population and a rurality index. The standard errors are reported below each estimate in parentheses and are bootstrapped in panel A . *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table A2: The effect of military interventions on public health transfers - excluding southern municipalities

Panel A: Panel data estimation

	(1)	(2)	(3)	(4)
	Dependent variable: Growth rate of SGP			
Model:	FE		2SLS	
asinh(Cocaine seizure)	0.0012	0.0006	-0.0000	-0.0147
	(0.0008)	(0.0007)	(0.0108)	(0.0115)
Department-year FE	Yes	Yes	Yes	Yes
Population share under subsidised regime	No	Yes	Yes	Yes
Colombian president × Prob. cocaine seizure	No	Yes	Yes	Yes
Right Governor × Prob. cocaine seizure	No	Yes	Yes	Yes
Municipality characteristics × year FE	No	Yes	Yes	Yes
ln(Municipality GDP)	No	Yes	Yes	Yes
ln(Population)	No	Yes	Yes	Yes
Observations	10355	10355	10355	10355
Municipalities	1036	1036	1036	1036

Panel B: First-stage of the corresponding 2SLS panel regressions

Dependent variable:	(3) asinh(Coca seizure)	(4) asinh(Coca seizure)
Prob. cocaine seizure × Growth(US Aid)	-5.0715***	-3.4648***
	(1.0370)	(0.8424)
Kleibergen-Paap F-statistic	23.92	16.91
Controls as in panel A	Yes	Yes

Notes: The results are obtained excluding observations from departments with weak State presence: Putumayo, Caqueta, Guaviare and Meta. FE estimates are obtained from equation (1) and reported in columns 1-2, and 2SLS estimates are shown in columns 3-4. Additional controls include distance to capital, number of health facilities in the municipalities, presence of oil and/or mineral resources, which are all interacted with year dummies, as well as the logarithm of population and a rurality index. Standard errors are below each estimate in parentheses and are adjusted for clustering at the municipality and department-year level. *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.