Beyond the Immediate: Cumulative Direct and Spillover Effects of Hot Spots Policing in Costa Rica*

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Abstract

This paper studies the effect of the "megaoperativos" security policy in San José, Costa Rica, using a weekly panel of crimes by district from 2018 to 2021. We find that the policy reduced violent crimes, car thefts, assaults, thefts, and property crime, and generated negative displacement effects in the surrounding districts where the policy was implemented. Furthermore, we find that the policy reduced total crimes by 2.35%, violent crimes by 3.67%, sexual offenses by 5.92%, assaults by 4.01%, aggressions by 1.95%, and thefts by 2.32% via its cumulative direct and spillover effects. Our results are consistent with a theoretical model that combines the microeconomic decision of a criminal to undertake criminal activities, with a macroeconomic problem that defines the probability of getting caught as an exogenous variable the agent observes in every period. Under this framework, we show that the effects of this policy compound in the long run and are consistent with a theoretical framework that models criminal deterrence and predicts strategic complementarity, i.e, the higher the crime levels, the smaller the probability of getting caught.

Keywords: crime, Latin America, public policy \ JEL Classification: O1, J08, J48

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Latin America is one of the most violent regions in the world without a war. The costs associated with crime in the region have been widely studied (Heinemann & Verner, 2006), and it has been estimated that it generates yearly costs between 2.41% and 3.55% of each country's GDP (Jaitman et al., 2015; Jaitman, 2017). Within Latin America, Central America is particularly violent; the number of intentional homicides for every 100,000 people is almost four times the world average (United Nations, 2017). Further, a history of civil wars and geographic proximity to cocaine markets have further fueled violence and crime by making firearms easily accessible (Oficina de las Naciones Unidos sobre Drogas y Crimen [UNODC], 2007; UNODC, 2012). Unfortunately, there is no evidence of the effectiveness of policies aimed at decreasing crime in the region.

In this paper, we study the effect of the "megaoperativos" (henceforth MOs) in San José, Costa Rica. The MOs are large police interventions that have been implemented all over the country since May 2018, and they constitute the country's most significant effort at tackling crime in recent years. We use weekly crime measures from 2017-2021 from the the capital city of San José. Our crime data comes from the 9-1-1 emergency system and the apprehension datasets from the Bureau of Judicial Investigations (OIJ in Spanish) and the Costa Rican police. The MOs data comes from confidential information systems of Costa Rica's police that indicate the place and time of the MO operations from 2018 to 2021.

With week-by-district panel data from 2017 to 2022, we estimate the direct cumulative and cumulative spillover effects of this policy over time. We estimate that via these two effects the policy reduced total crimes by 2.35%, violent crimes by 3.67%, property crimes by 1.03%, car thefts by 2.15%, sexual offenses by 5.92%, assaults by 4.01%, aggressions by 1.95%, and thefts by 2.32%. These results are consistent with findings in recent literature reviews (Bowers et al., 2011; Braga et al., 2012; Weisburd & Telep, 2014; Abd & Winship, 2016; Chalfin & McCrary 2017; Braga et al., 2019) and single case studies (Braga & Bond, 2008; Braga et al., 2012). In addition to estimating the cumulative effects of the policy, our panel dataset also allows us to estimate the effect of having MOs in the current week conditional on the cumulative number of MOs a district has had up to a certain week. We call these the *instantaneous effects*, and we argue that they capture the mechanical effects of higher reporting of crimes due to a larger police presence. We find that conditional on the cumulative number of MOs, there are no instantaneous MO nor spillover effects. This is evidence that "hot spots" policies yield their effects over time through the accumulation of treatment and their intensity.

This work makes several significant contributions to the literature on criminal deterrence.[1] In particular, our paper complements papers that study the effects of "hot spots" policing. Multiple literature reviews (Bowers et al., 2011; Braga et al., 2012; Weisburd & Telep, 2014; Abd & Winship, 2016; Braga et al., 2019) and case studies (Braga & Bond, 2008; Braga et al., 2012) covering RCTs and quasi-experimental designs have found that these types of policies have been effective at reducing crime, while there is little to no evidence of displacement effects from hot spots policies. While the literature suggests that the effectiveness of police interventions depends on the context and particular actions taken (Lazzati & Amilcar, 2016), the consistent finding is that when these interventions are focused on precise locations and moments of high criminal activity, they are effective at reducing crime (Sherman, 1992; Weisbund & Eck, 2004; Abd & Winship, 2016; Kennedy et al., 2018). Our work also addresses a limitation regularly cited in the literature, which is the absence of long-run effects. Because we use a panel dataset over a span of 4 years, our work makes a unique contribution to the literature by showing that the MOs policy has effects that compound over time.

[1]See Chalfin & McCrary (2017) for an extensive review of this literature.

We also contribute to the literature by proposing a theoretical model that explains how MOs can affect crime over time via cumulative effects. We model a representative agent who makes a simple decision every period between the amount of crime and labor he/she decides to undertake. The probability of getting caught is a variable that all agents take as exogenous every period. This probability depends on the state of the economy, the relative number of police officers, and the total level of crime in the economy. Furthermore, this probability depends on the previous history of these variables, thus creating changes that compound over time and change the optimal decision of the agent in every period. The model predicts that the MOs policy will have cumulative effects over time and will generate spillovers over time and space. Furthermore, the model also predicts that the higher intensity of treatment over time also will generate larger reductions in the level of crime over time via cumulative MO and associated spillover effects. Besides creating testable hypotheses, this model also motivates the empirical approach used in this work, and can help evaluate similar hot spots policies in other contexts.

This work also fills a gap in the literature on the effectiveness of security policies on crime in developing countries. One of the few works in this area is an RCT in India (Banerjee et al., 2019) that found that randomized police controls on roads and highways decreased car accidents due to excessive alcohol consumption by 25%. For Medellín, Colombia (Collazos et al., 2021), another RCT found significant decreases in criminality in places where more police were allocated with no displacement effects. For Buenos Aires, Argentina (Di Tella & Schargrodsky, 2004), the increase in the number of police officers around Jewish and Muslim religious centers after a terrorist attack decreased crime in these areas without creating displacement effects. A more recent RCT for Bogotá, Colombia, found that an increase in officers moderately decreased crime but generated significant displacement effects (Blattman et al., 2021).

Finding effective security policies would contribute to tackling the various costs of crime in Latin America. Previous studies have found that crime has significant negative consequences on the price of homes (Aizenman et al., 2015; Vetter et al., 2018), labor participation and employment (Robles et al., 2013), labor productivity (Cabral et al., 2016), the growth of small businesses (BenYishay & Pearlman, 2014) and economic growth (Enamorado, 2014; Estrada & Ndoma, 2014). Likewise, there is evidence that crime negatively affects trust in democracy and democratic institutions (Blanco, 2013) and the well-being of newborns and children in general (Agüero, 2013; Manacorda & Koppensteiner, 2013). Although the evidence from developing countries and Latin America seems to be consistent with what has been found in developed countries, there are no studies in Central America. This is a region with various social problems that end up fueling crime and violence. For instance, it is estimated that 90% of the cocaine exports to the United States. go through the region (UNODC, 2007), and while 77% of homicides are undertaken with firearms, more than half of the weapons are not registered (UNODC, 2012). All of these issues have created a poverty trap, where violence and crime disincentivize investments, which fosters youth unemployment and creates ideal conditions for drug trafficking (UNODC, 2012). Furthermore, Central America has not seen a reduction in crime from 2015 to 2020 (PEN, 2021) and, its income inequality has worsen to the point where the current Gini index is close to 0.5 (World Bank, 2021). In addition, the lack of dissemination of information has limited debates on policies that could contribute to the reduction of crime (RESDAL, 2013).

Costa Rica in particular has not seen any reduction in crime levels in the last decade. Since 2010 most types of crimes have had a steady behavior, with more than 500 homicides and over 7,000 house robberies every year (Observatorio de la Violencia, 2020, 2021). Furthermore, related crimes have almost doubled over the last decade, from 50,000 a year in 2010 to more than 98,000 in 2019. The level of crime per capita in the

country has increased significantly since the late 90s, when the murder rate was 4 per 100,000 people, and climbed to over 10 in 2010 (Mata & Solano Fernández, 2006; INEC 2019). Adding to these grim figures, poverty and income inequality have essentially remained
unchanged since the late 1990s. More specifically, the Gini coefficient has not been lower than 0.5 since 2008 and poverty levels have fluctuated at around 20% (INEC, 2021). Therefore, studying the effectiveness of the most important security policy the country has implemented in its recent history is of great importance for the overall welfare of Costa Rica and public policy debates regarding crime and security policies.

The rest of the paper proceeds as follows. In the following section, we provide a brief description of the megaoperativos policy. We then present our theoretical framework along with its predictions and implications. The following section discusses the data and empirical approach used in this work. After this, we present our results and robustness checks. And finally, we present a discussion and conclusions about our work.

The megaoperativos hot spots policy

The megaoperativos (MOs) are a nationwide security policy that Costa Rica's police implemented from May 2018 until May 2022. They consist of police operations that usually last anywhere between 10 and 12 hours where the number of police officers is increased significantly in strategic locations, and special police units are deployed (MSP, 2020a, 2020b, 2021a, 2021b)[2].

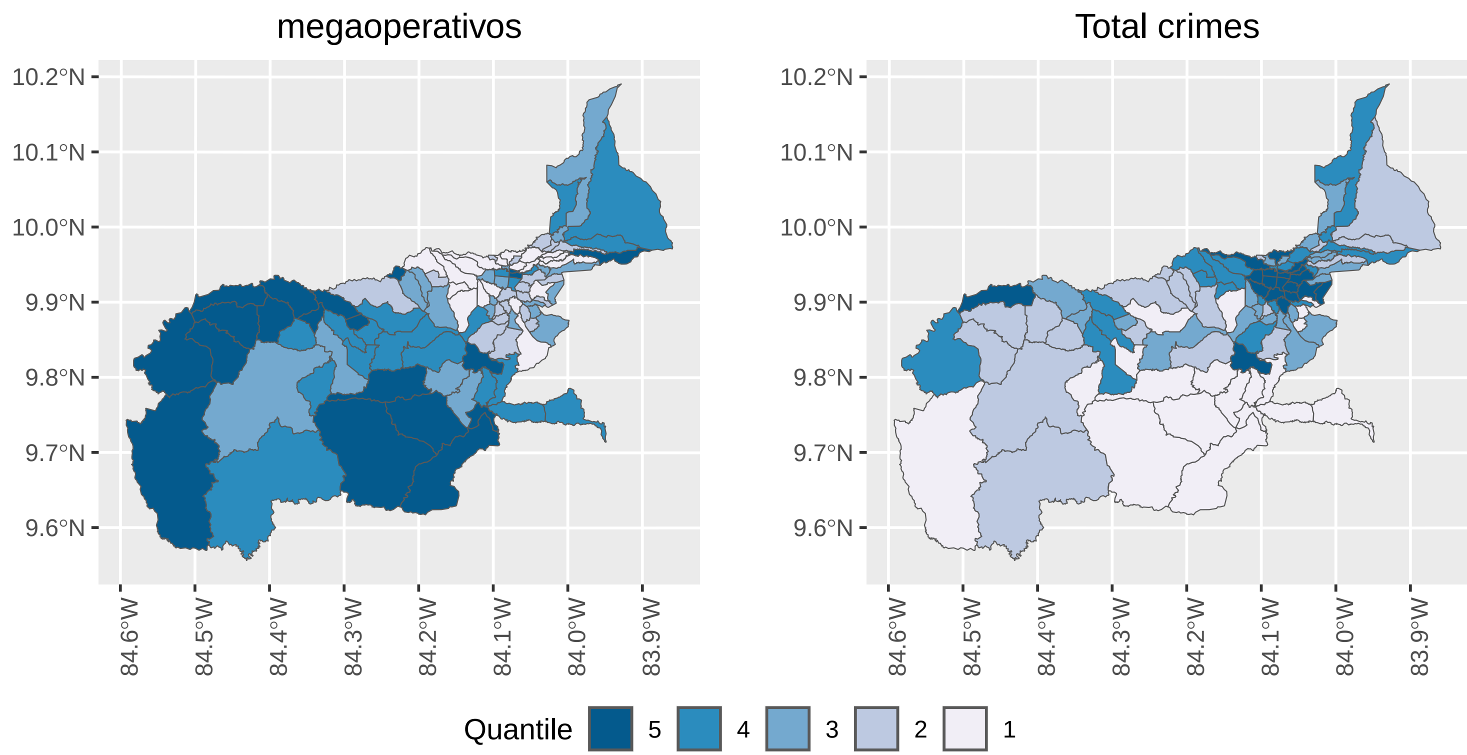
Both the police force and the Costa Rican government have claimed that these interventions have represented some of the biggest efforts by Costa Rican authorities to tackle crime in the country, and their implementation has been linked to multiple drug and firearms busts, arrests, and confiscation of contraband items all over the country. Figure 1 shows the distribution of per capita megaoperativos and total crimes over the area of study in this work, which includes the capital city of San José and its surrounding areas. The figure first demonstrates there is significant spatial variation in treatment and outcomes. The higher number of per capita MOs occur in the areas to the east and west of downtown San José, which are larger districts and more rural areas. On the other hand, the areas with the most crimes per capita are the ones in downtown San José and the immediate surrounding areas. These are areas with higher concentrations of economic activity and population density.

Authorities decide the place and location of MOs based on police intelligence, crime heat maps, knowledge of the areas to be patrolled, and feedback from the national security policy. Nonetheless, as shown in Appendix 2, MOs tend to be implemented on Fridays and Saturdays. Furthermore, there is a higher concentration of MOs in the last three months of the year. These stylized facts most likely reflect the fact that weekends and the end of the year are the periods when there is a higher need for security services for the population and hence police officers react accordingly.

Besides being implemented all over the country, MOs take place throughout the entire year. To give an idea of the intensity of these operations, Figure A1 shows that more than 70% of all MOs have lasted at least 10 hours, while Figure A2 demonstrates that MOs are concentrated around weekends and during the final months of the year.

[2] Appendix 1 shows that approximately 70% of all megaoperativos last at least 10 hours.

Figure 1: Per capita megaoperativos and total crimes by district, 2018-2022



Notes: The map on the left displays the number of per capita number megaoperativos by district and quantile. The darker districts are those in the fifth quantile, i.e, in the top 20% of the total number of megaoperativos per capita. The lighter districts are in bottom 20% of the total number of megaoperativos per capita. The map on the right displays the total number of per capita crimes by district and quantile. The darker districts are those in the fifth quantile, i.e, in the top 20% of the total crimes per capita. The lighter districts are in the bottom 20% of the total crimes per capita.

Theoretical framework

This section presents a theoretical model that explains how the MOs affect the levels of crime via direct and spillover effects, while also explaining the dynamics of MOs and their effects over time. Each agent in the economy decides in each period the amount of crime they commit. The MOs constitute a macroeconomic policy for the individual agents in this economy. In any given period, the probability of getting caught depends on the state of the economy, the relative number of police officers, and the total amount of crime in the economy. Changes in any of these variables change the probability of getting caught, which in every period readjusts the decisions of every individual. The choice is the same for every agent in every period. But the decisions vary across agents due to differences in their outside options and payoffs from crime. The model explains the dynamics of the MOs as well as their direct and spillover effects. In addition, the model suggests multiple testable hypotheses.

We begin by presenting the microeconomic problem each agent faces. The individual decision follows closely the setup by a simple model of crime waves, riots, and revolutions (Tabarrok, 1997). There are n agents, indexed by i where $i = 1, 2, ...n$. Each agent is located in a district k where $k = 1, 2, ...m$, and we assume that there is no migration. The individual's utility is a function of wealth, $U_{i,k}(W_i)$, where $U'(W) > 0, U''(W) < 0$. Each agent chooses how much time to devote to crime $c_{i,k}$ and noncriminal activities $l_{i,k}$. If the agent chooses to commit some crime, they face a probability of punishment $p_k(C)$. This probability depends on the total level of crime in the economy, where $C = \sum_{k=1}^{m} C_k$, and where each C_k refers to the total level of crime in district k. The probability also depends on the state of the economy Y, and the total number of police officers in the district Γ_k with respect to the population. We assume that each agent is small with respect to the total economy and the district where they are, therefore each agent takes the level of crime in their region C_k, the total level of crime C, the state of the economy Y and the number of police officers Γ_k and the probability of getting caught $p_k(C, Y, \Gamma_k)$ as given.

There are two states of nature for the agent: the agent gets punished, and the agent does not get punished. The respective levels of wealth in each state are represented as follows:

$$W_p = W_o + W_c(c_{i,k}) + W_l(l_{i,k}) - F(c)$$

$$W_{np} = W_o + W_c(c_{i,k}) + W_l(l_{i,k})$$

W_o is initial wealth, $W_c(c_{i,k})$ is wealth from criminal activity, $W_l(l_{i,k})$ is wealth from working in noncriminal activities, and $F(c_{i,k})$ is the fine or punishment the individual faces when they are punished. We assume the following about these wealth components:

$$\frac{\partial W_c}{\partial c}, \frac{\partial W_l}{\partial l}, \frac{\partial F}{\partial c} > 0, \frac{\partial^2 W_c}{\partial^2 c}, \frac{\partial^2 W_l}{\partial^2 l} < 0 \ \ and \ \ \frac{\partial^2 F}{\partial^2 c} > 0$$

The strategy choices for every agent constitute a Nash equilibrium if for every agent i, $c^*_{i,k}$ maximizes their expected utility:

$$\max_{c_{i,k}} EU_i = \max_{c_{i,k}} p(C, Y, \Gamma_k)U(W_p) + (1 - p(C, Y, \Gamma_k))U(W_{np}) \tag{1}$$

Choosing $c_{i,k}$ yields the following first order condition for each agent i:

$$\frac{p_k(C,Y,\Gamma_k)U'(W_p)}{(1-p_k(C,Y,\Gamma_k))U'(W_{np})} = -\frac{W_c' - W_l'}{W_c' - W_l' - F'} \tag{2}$$

We can rearrange this equation:

$$\frac{U'(W_p)}{U'(W_{np})} = -\frac{(W_c' - W_l')(1-p_k(C,Y,\Gamma_k))}{(W_c' - W_l' - F')(p_k(C,Y,\Gamma_k))} \tag{3}$$

This result shows that each agent will equate the marginal rate of substitution between being punished and not punished with the ratio of marginal benefits and costs of committing criminal and noncriminal activities weighted by the probability of getting caught in district k. *Ceteris paribus*, an increase in the probability of getting caught makes the agent choose to engage in fewer criminal activities and more noncriminal activities.

The relative number of police officers (Γ_k), the level of crime in the district (C_k), the total level of crime in the economy (C), and the state of the economy (Y) are macroeconomic variables that in any given period every agent i in any district k takes as exogenous. These variables in turn affect the individual via changes over time in the probability of getting caught. Hence, the probability of getting caught $p_k(C,Y,\Gamma_k)$ generates the dynamics in this model.

We now proceed to model the dynamics of $p_k(C,Y,\Gamma_k)$. We first assume that the change in probability can be expressed as a linear first order differential equation:

$$\dot{p_k} = ap_k + \beta\Gamma_k + \delta Y + \lambda f(C_1, C_2, ..., C_k) \tag{4}$$

All of these variables depend on period t, but we drop t to simplify notation. $\dot{p_k}$ is the change in the probability of getting caught in district k. Γ_k is the number of police officers in district k, Y is the state of the economy, and $f(C_1, C_2, ..., C_k)$ is a continuous, differentiable, and increasing function in each of its parameters that depends on the total levels of crime in the economy. Furthermore, we also assume that the level of crime in each district C_k is affected by the number of police officers Γ_k and intrinsic non-time varying characteristics for each districts I_k. Therefore, we can express $f(C)$ as $f(C_1(\Gamma_1, I_1), C_2(\Gamma_2, I_2), ..., C_k(\Gamma_k, I_k))$. α, β, δ, and λ are parameters that measure the marginal effect of each of these variables on the change of the probability of getting caught.

We solve the equation:

$$\dot{p_k} - \alpha p_k = \beta\Gamma_k + \delta Y + \lambda f(C_1, C_2, ..., C_k) \tag{5}$$

By multiplying each side by an integrating factor and rearranging:

$$\dot{p_k}e^{-\alpha t} - \alpha p_k e^{-\alpha t} = [\beta\Gamma_k + \delta Y + \lambda f(C)]e^{-\alpha t}$$

$$p_k = [\int_0^t [\beta\Gamma_k + \delta Y + \lambda f(C)]e^{-\alpha s} ds]e^{\alpha t} \tag{6}$$

This solution for p_k suggests a difference between contemporaneous and cumulative effects of MOs. On the one hand, contemporaneous effects at a given period τ are given by the partial derivatives of this expression with respect to each variable while holding the period constant. The instantaneous effects of more police officers in district k, and the contemporaneous spillover effects of more police officers in a different district j are given by:

$$\frac{\partial p_k}{\partial \Gamma_k} = [(\beta + \lambda \frac{\partial f(C)}{\partial C_k} \frac{\partial C_k}{\partial \Gamma_k}) e^{-\alpha t}] e^{\alpha t} = \beta + \lambda \frac{\partial f(C)}{\partial C_k} \frac{\partial C_k}{\partial \Gamma_k} > 0 \tag{7}$$

$$\frac{\partial p_k}{\partial \Gamma_j} = [(\lambda \frac{\partial f(C)}{\partial C_j} \frac{\partial C_k}{\partial \Gamma_j}) e^{-\alpha t}] e^{\alpha t} = \lambda \frac{\partial f(C)}{\partial C_j} \frac{\partial C_j}{\partial \Gamma_j} > 0 \tag{8}$$

Equations (7) and (8) are the instantaneous effects of increasing the number of police officers -implementing an MO in the context of this work- in district k and in a different district j respectively. In equation (7), β captures the effect of having more police officers in the district. We would expect that β is positive, since the more police officers are present in a district, the more likely that a criminal will be caught committing a crime. $\lambda \frac{\partial f(C)}{\partial C_k} \frac{\partial C_k}{\partial \Gamma_k}$ captures the crime reducing effect that more police officers have in the district. $\frac{\partial f(C)}{\partial C_k} > 0$ by assumption and, $\frac{\partial C_k}{\partial \Gamma_k} < 0$ since it indicates that crime will be reduced the more police officers are operating in the district. This implies that λ is negative for equation (7) to be positive. This is not only an algebraic necessity, it also makes intuitive sense. Since $f(C)$ is positive and increasing in all its parameters by assumption, when any of these increase the probability of getting caught has to decrease. Along similar lines, equation (8) is also positive: a higher number of police officers in another district j lowers the levels of crime in district j. This lowers crime everywhere in the economy, which increases the probability of getting caught.

Following a similar procedure, we can demonstrate the cumulative effects. These are a product of computing the change in p_k up to a period of interest τ and determining how this effect accumulates over time. The cumulative effects of more police officers in district k, and the cumulative spillover effects of more police officers in a different district j are given by:

$$\frac{\partial p_{k,\tau}}{\partial \Gamma_{k,\tau}} = [\beta + \lambda \frac{\partial f(C)}{\partial C_k} \frac{\partial C_k}{\partial \Gamma_k}] e^{\alpha(t-\tau)} \tag{9}$$

$$\frac{\partial p_{k,\tau}}{\partial \Gamma_{j,\tau}} = \lambda \frac{\partial f(C)}{\partial C_j} \frac{\partial C_j}{\partial \Gamma_j} e^{\alpha(t-\tau)} \tag{10}$$

The difference between the spillover and the instantaneous effects is the $e^{\alpha(t-\tau)}$ component. Intuitively, this says that the more time has passed -the bigger difference between t and τ- the larger the cumulative effects. For these equations to reach a steady state equilibriums, we require that $-1 < \alpha < 0$. Given this restriction for the model, we can ascertain that the cumulative effects in equations (9) and (10) are larger than the instantaneous effects in equations (7) and (8). Furthermore, if we hypothesize that the MOs only create meaningful effects on the levels of crime via an increase in the probability of getting caught p_k, we expect β and λ to be small. Hence, what creates a meaningful change in the probability of getting caught is the cumulative nature of p_k over time.

Although equations (9) and (10) describe the nature of the cumulative effects, it is not clear if the MOs cumulative effect will be larger, equal to, or smaller than the cumulative spillover effects. However, given the nature of the policy we further assume that:

$$\exists x \in q = 1, 2, ...m \wedge j \neq k \; s.t.: \qquad \frac{\partial^x p_{k,\tau}}{\partial^1 \Gamma_{1,\tau} \partial^2 \Gamma_{2,\tau} ... \partial^x \Gamma_{j,\tau}} > \frac{\partial p_{k,\tau}}{\partial \Gamma_{k,\tau}} \tag{11}$$

In other words, as the number of MOs increases, we assume there is a number at which the cumulative spillover effects are bigger than the MO cumulative effects. We call this prediction the *multiplicative spillover effect*. In other words, the more MOs surround a district, the stronger the spillover effect. We believe this is a reasonable conjecture within the context of the policy, since in any given week spillover districts are surrounded by multiple treated districts. As a matter of fact, in weeks where an MO is implemented, the average spillover district is surrounded by 12.1 districts that implemented at least one MO. Furthermore, a second conjucture is that if the number of times a district is a spillover is high enough over time, this would also imply that at any given period the cumulative spillover effects are larger than the MOs, direct effect.

This model also exhibits positive spillovers, i.e, an agent's expected utility is increasing in the amount of crime committed by other agents, regardless if they are in the same district or not:

$$\frac{\partial EU_i}{\partial C_j} = \frac{\partial P_k}{\partial f(C)} \frac{\partial f(C)}{\partial C_j}(U(W_p) - U(W_{np})) = \lambda \frac{\partial f(c)}{\partial C_j}(U(W_p) - U(W_{np})) > 0$$

More intuitively, if there is more total crime in the economy , this lowers the probability of getting caught in all districts and increases the expected utility of agent i. These are the spatial spillovers that our theoretical framework predicts. The model also exhibits strategic complementarity, i.e, an agent's optimal strategy is increasing in the strategy choices of other agents. Taking the derivative of the first-order condition with respect to the choices of the other agents, one finds this effect compounds the more changes in crime the agent sees in the economy:

$$\frac{\partial EU_i}{\partial c_{i,k} C_j} = \frac{\partial P_k}{\partial f(C)} \frac{\partial f(C)}{\partial C_j}[U'(W_p)(W'_c - W'_l - F') - U'(W_{np})(W'_c - W'_l)] > 0$$

$$\frac{\partial EU_i}{\partial c_{i,k} C_j} = \frac{\partial P_k}{\partial f(C)} \frac{\partial f(C)}{\partial C_j} \frac{1}{\partial p_k(C, Y, \Gamma_k)} = -\lambda \frac{\partial f(c)}{\partial C_j} \frac{1}{p_k(C, Y, \Gamma_k)} > 0$$

In sum, our model predicts that changes in the levels of crime in any district will change the probabilities of getting caught in every district. The probability of getting caught p_k is the key variable in the model. In addition, the model also shows how cumulative and contemporaneous effects affect the levels of crime in the economy. One period changes in variables are compounded over time and influence the probability of getting caught committing a crime in future periods.

The same logic applies to the other variables considered in the model: the state of the economy Y and the relative levels of police officers in the district Γ_k. For example, the changes in the economy due to the COVID-19 pandemic can be seen as a sudden massive drop in the state of the economy Y and a higher number of police officers in the street relative to the population Γ_k. In tandem, these two effects increase the probability of getting caught and thus lower the number of crimes seen in the economy. These shocks affect the contemporaneous probability of getting caught, but also its future levels. Since agents observe less crime in the economy, they interpret that the probability of getting caught has gone up, and so on.

Data and summary statistics

Datasets

We use four day by hour datasets to analyze the effect of MOs on the levels of crime in San José, Costa Rica:

Crime base of the Bureau of Judicial Investigations

The Bureau of Judicial Investigations (OIJ) is an institution that is the part of Costa Rica's judicial system in charge of conducting criminal investigations on its behalf. This dataset includes all the crimes that were filed and investigated in Costa Rica from January 2017 until October 2021. For each crime, we have information on: the type of crime and the day, hour and district where it took place. From this dataset, we use the following crimes: car thefts, assaults, aggressions, thefts, robberies, sexual offenses, and homicides.

9-1-1 Emergency system database

This dataset contains all the incidents to the 9-1-1 emergency system that involved Costa Rica's police force from January 2017 until December 2020. For each crime incident reported, we have information on: the type of incident and the day, hour and district where it took place. From this dataset, we use the following crimes: firearms incidents and domestic violence incidents.

Costa Rica's police force drug apprehensions dataset

This dataset contains information on the drug apprehensions that Costa Rica's police officers undertook from January 2017 until December 2020. For each apprehension, we have information on the type of incident and the day, hour and district where it took place. This dataset also contains information on the amounts of drugs that were collected from each apprehension. From this dataset, we extract the following crimes: cocaine apprehensions, crack apprehensions, marijuana apprehensions, confiscated cocaine grams, confiscated crack grams and confiscated marijuana grams.

megaoperativos database

We were granted access to the confidential database that contains the information for each MO in the capital city of San José from May 2018 to December 2021. This data is stored in various PDF files in a computer that is not connected to the internet, and where it is not allowed to download any of the information. This is highly sensitive information that contains names, number and types of weapons, and details on operational logistics, among many other types of sensitive information. We were allowed to manually check every PDF and collected the hours, exact location, and date of each MO in the 2018-2021 period. Knowing the exact location entails gathering the street address or point of reference (bar, school, cultural landmark, building) where each MO started. This allows us to pinpoint the exact district that is being treated by the MO.

Summary statistics

Using the datasets described in the previous section, we proceed to create a balanced weekly panel at the district level from 2017 to 2021. More specifically, we work with 99 districts in the province of San José, which cover all of the Costa Rican capital's downtown as well as its suburbs and nearby rural areas. In any given period, this area comprises more than 80% of all the crime in the country.

We focus on four main categories of crime: total crime (violent crime plus property crimes), violent crimes (assault, aggressions, and homicides), property crimes (robberies, thefts, and car thefts) and car thefts. We chose these categories because the aggregation of categories can attenuate measurement error and better capture trends in crime over time. We also chose car theft because it is arguably one of the best measured types of crime.

Figure 2 provides suggestive evidence about the effectiveness of MOs at reducing crime where we plot the weekly number of total crimes and the total number of MOs from May 2018 to December 2021. Prior to the policy being in effect, the total number of weekly crimes had a slight increasing trend over time. When MOs start being implemented the number of weekly crimes jumps. This is a change observed in all types of crimes[3] except car thefts and firearms incidents. This suggests that this jump in the number of crimes in May 2018 may be due to a mechanical reporting effect, i.e, since there are more police officers in the street, more crimes are detected. As time advances, there is a decreasing trend in the number of weekly crimes as the number of MOs is increased until February 2020. This is something that is observed for most of the crimes considered and is consistent with an expected deterrence effect due to a larger and more intense police presence created by the MOs.

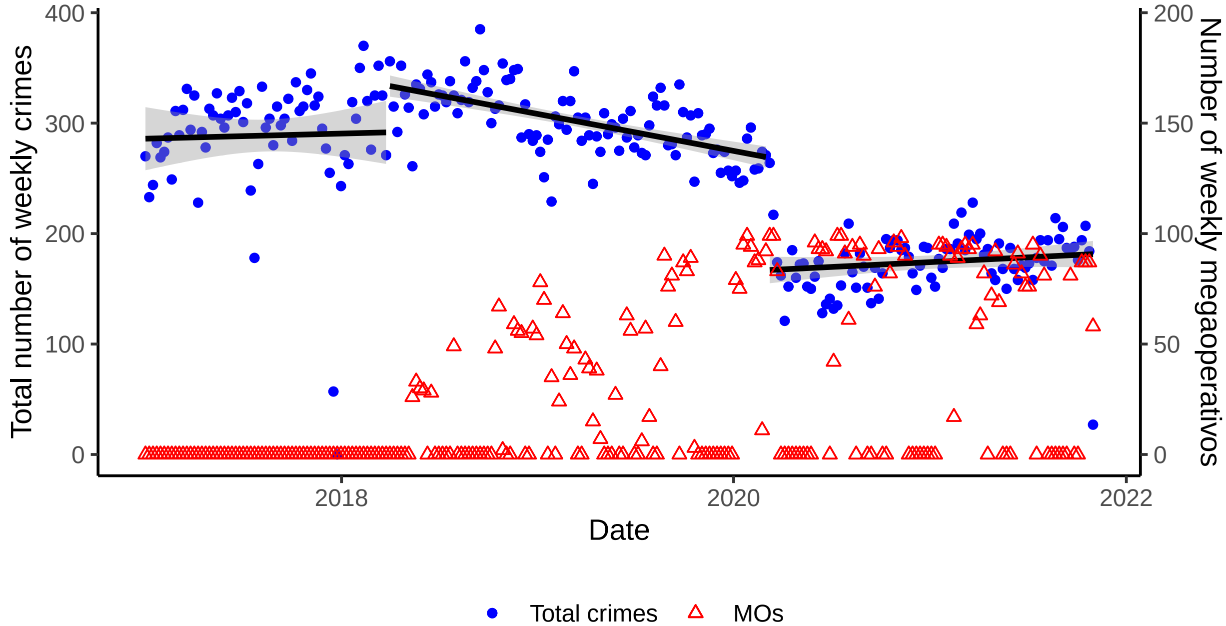
In March 2020, due to the COVID-19 pandemic we see a sudden decrease in the levels of weekly total crimes. This is to be expected, as this pandemic shock constitutes an inhabilitation effect on crimes in the economy; i.e, the decrease in crime is due to the removal of a significant number of potential criminals from society. The increasing trend in the number of weekly MOs ceased to continue during the pandemic, while the number of total crimes remained the same. This suggests that the MOs maintained the number of crimes at a lower level than the one at which they were in the pre-pandemic period. Similar behavior can be seen for violent crimes, car thefts, assaults, aggressions, domestic violence incidents, and firearms incidents.

Regarding intensity of treatment, on average, districts were treated 28% of the weeks under analysis (51 out of 183). For treated districts, the average duration of MOs was 14.75 hours. On average, districts were spillover districts 34% of the weeks under analysis (65 out of 183). Similarly, in a week where a district was a spillover, it was surrounded by on average 12 districts that at least implemented one MO, while the average number of *spillover hours*[4] was 62.7. We show in Appendices 3 and 4 how these MO and spillover hours are distributed geographically, where most of these hours are concentrated in the downtown districts of San José and the immediate surrounding districts. Appendices 5 and 6 further confirm this trend, where the top five districts in MO and spillover hours are districts in the downtown area of San José.

[3] We show similar plots for the other crimes considered in this work in the appendix from figures A7 to A20 to save space in the main document.

[4] The summation of the duration of the MOs in the surrounding districts.

Figure 2: Megaoperativos and total crimes by week



Notes: Plot shows the total number of violent crimes in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of violent crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Empirical approach

We seek to identify the cumulative direct and spillover effects of MOs on crime. To do this, we apply a two-way fixed effects model using controls for instantaneous effects (contemporaneous effects in the theoretical framework). The estimation equation is the following:

$$\begin{aligned} crime_{it} = \beta + \beta_1 CumMO_{it} + \beta_2 CumSpillover_{-it} + \beta_3 MO_{it} + \beta_4 Spillover_{-it} + \\ \beta_k^{'} X_k + \psi_t + \eta_i + \epsilon_{it} \end{aligned} \tag{12}$$

$crime_{it}$ is the number of crimes in district i in week t. We standarize this variable to make the comparison between estimates easier. $CumMO_{it}$ is the number of cumulative MOs up to week t in district i. $CumSpillover_{-it}$ is the number of cumulative times district $-i$ has been next to a district that was treated up to week t. If a district is being treated, it cannot be a spillover district. MO_{it} is a dummy variable which indicates if in week t, district i had at least one MO or not. This is the instantaneous effect of the MOs. $Spillover_{-it}$ is another dummy variable indicating if in week t, district $-i$ was next to a district that received at least one MO. This is the instantaneous spillover effect.

X_k is a set of week-by-district controls which include: total rainfall in milliliters, total length of MOs in hours, number of times a spillover district is surrounded by treated districts, number of MOs that were "road controls"[5], and number of times MOs started on one day and finished on the next day. psi_t are time fixed

[5]Some megaoperativos are known in Spanish as *controles de carretera*, which loosely translates to "road controls". These

effects. In our estimates, we consider three different levels of time fixed effects: no time fixed effects, month by year fixed effects, and week by year fixed effects. We present the estimates with no time fixed effects as a reference with respect to models that control for time trends, and thus shows the advantage of fully using the attributes of a panel dataset. Finally, η_i are district fixed effects. All of our regressions are estimated with OLS and we cluster errors at the district level. The use of both time fixed effects and district fixed effects aid us in addressing omitted variable bias that may arise from intrinsic non-time varying characteristics (I_k) and time varying characteristics (ψ_k).

In the main manuscript, we present the results counting the number of MOs (extensive margin) rather than *MO-hours* (intensive margin). We briefly analyze these results in the robustness checks and discussion sections of this document. Our conclusions do not change if we analyze the intensive margin, and we show these results in the appendix.

Following our theoretical framework, β_1 and β_2 correspond to the predictions of equations (9) and (10) of our theoretical framework. We hypothesize that the MOs policy only has effects on crime through the cumulative effect of the MOs and their respective spillovers over time. β_3 and β_4 are the instantaneous effects shown in equations (7) and (8). Conditional on the cumulative number of MOs and spillover effects, we would expect β_3 to be zero, or positive. In the case that β_3 is positive, it is capturing a mechanical reporting effect due to a larger police presence, i.e, since there are more police officers in the street, more crime is reported. If β_3 is zero, it implies that there is no instantaneous effect of the policy. This is consistent with our theoretical framework, because conditional on the cumulative number of MOs and spillovers, one should not expect crime levels to be different than what one would observe regardless of the presence or intensity of the policy. Finally, we expect β_4 to be not different from zero because the policy should have effects via its cumulative effects, and also, one should expect that places that remain untreated will not experience a change in their levels of crime.

Causal identification requires that the covariates are not correlated with the error in any period. Although this cannot be proven directly, we provide evidence that gives us more confidence in our results. First, we conduct a "pre-trend" test, where we interact the cumulative number of MOs with a time trend before the MOs take place. We then estimate this model with and without controls. If this test is different from zero, it provides evidence that conditional on our controls, police officers are not self-selecting into districts with more or less crime.

The results of this test for the main outcomes of interest are shown in Table 1. Without any controls, we find that districts that accumulated more MOs had lower levels of crime prior to the policy being implemented. These results alone would suggest that police officers choose to conduct MOs in districts with lower levels of crime. One could speculate that this is done for the purpose of making the MOs look more effective than they actually are. However, upon adding our set of controls and fixed effects, we see that this pre-trend coefficient is not different from zero. This supports the idea that once the policy is put into place, MOs are conditionally as good as random.

are MOs in which police officers do not conduct any additional patrols but instead place themselves on strategic roads and conduct vehicular stops and searches. These MOs can take place within the execution of other MOs or they can be an MO of their own.

Table 1: Pre-trend period, 2017-2018

	Panel A: No controls estimates			
	Total crimes	Violent	Property	Car theft
	(1)	(2)	(3)	(4)
Pre-trend	-0.00001^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
District FE	No	No	No	No
Year-week FE	No	No	No	No
Observations	5,247	5,247	5,247	5,247
	Panel B: Fully controlled estimates			
	Total crimes	Violent	Property	Car theft
	(1)	(2)	(3)	(4)
Pre-trend	0.00000	0.00001	-0.00001	0.00000
	(0.00001)	(0.00001)	(0.00001)	(0.00000)
District FE	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes
Observations	5,247	5,247	5,247	5,247

Notes: the table shows the coefficient estimates for the main types of crimes of the interaction between the total cumulative number of MOs and a time trend before the MOs are implemented. Panel A shows the estimated coefficients when the regression does not include any control variables. Panel B shows the estimates once all district and time fixed effects are included in the regressions. *p<0.1; **p<0.05; ***p<0.01.

We show this test for all of the selected crimes in the appendix (Appendices 21 and 22). For all crimes except robbery, we find that upon controlling for time and district fixed effects the MOs are conditionally as good as random. Overall, we find robust support for the claim that police officers did not conditionally self-select into districts with more or less crime. Another concern is that agents may know when an MO is going to happen. We test for such anticipatory effects and fully discuss them in the robustness checks later on in this document.

Results

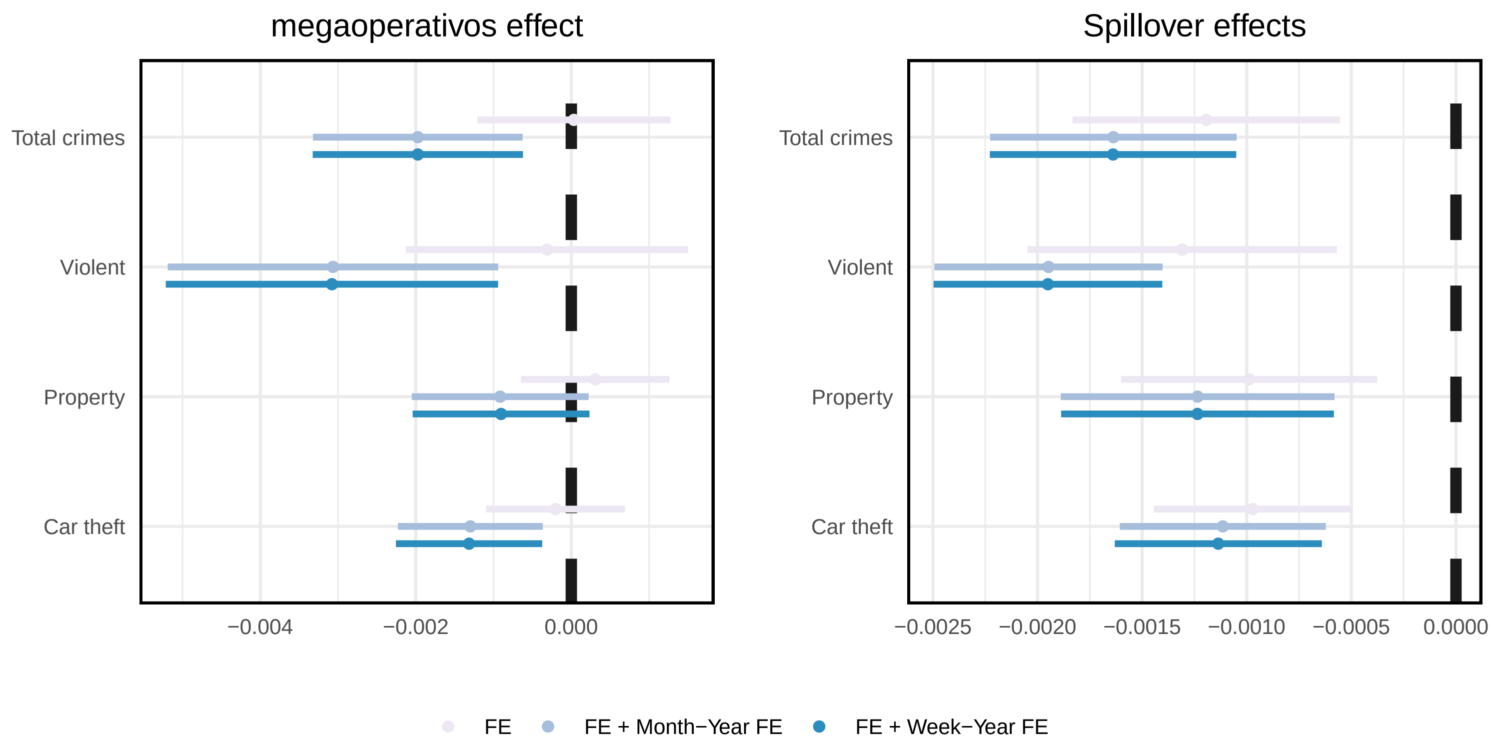
Cumulative effects

We begin our analysis with the cumulative effects results for the main outcomes of interest in Figure 3. The *megaoperativos cumulative effect* is shown on the left panel and the *spillover cumulative effects* on the right panel. For each type of crime we show the point estimates of β_1 and β_2 of equation (12) along with the confidence interval at a 95% significance level.

In our preferred specification we find significant negative effects for total crimes, violent crimes, and car thefts. An additional cumulative MO decreases the total number of crimes by -0.002 of one standard deviation of total crimes. Since the standard deviation of the total number of crimes is 6.51 and the average number of MOs per week is 2.85, this implies that on average MOs reduce total crimes by 0.036 each week. With respect to the average of 3.43 total crimes per week, this effect represents a reduction of 1.06% in the number of total crimes per week. Following the same exercise for the spillover coefficient of -0.0016, and considering that there are on average 4.38 district spillovers per week, this implies that via spillover effects on a weekly basis total crimes is reduced by 1.35%. By adding the megaoperativos (MOs) cumulative effect and the spillover cumulative effects, we obtain that on average the MO exposure reduces total crimes by 2.41% every week.

Applying the same calculations for the other crimes in Figure 3, we find that via the cumulative MO effect, violent crime is reduced by 1.86% and car thefts are reduced by 0.92% on an average weekly basis, while via the spillover cumulative effect, violent crimes are reduced by 1.81%, property crimes by 1.03% and car thefts by 1.23% on a weekly basis. Therefore, our results indicate that in total MOs on average reduce total crimes by 2.41%, violent crimes by 3.67%, property crimes by 1.03%,

Figure 3: Cumulative effects, extensive margin.



Notes: The left image shows the point estimates for the cumulative effects of an additional megaoperativo along with their 95% confidence intervals. The right image shows the point estimates for the cumulative spillover effect of an additional megaoperativo on crime in districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

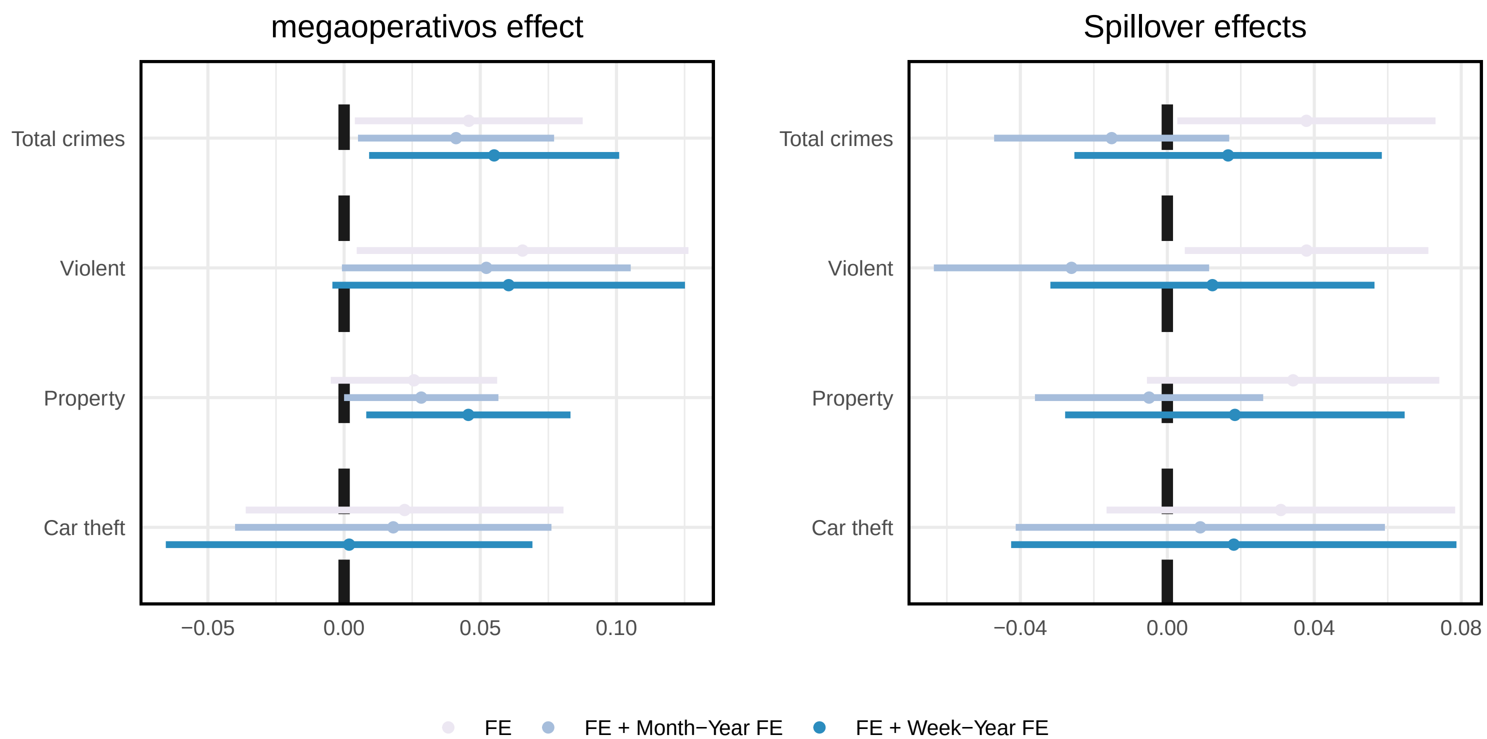
Instantaneous effects

In Figure 4, we show the instantaneous MO and spillover effects. These correspond to the estimates of the β_3 and β_4 of equation (12). Given our theoretical framework and the nature of the data, we expect β_3 to be either zero or positive, which suggests the existence of reporting effects, while we expect β_4 to be zero.

For total crimes, violent crimes (at the 10% significance level), and property crimes, we find positive instantaneous effects. Since the regression already includes the cumulative effects, these positive effects are picking up the mechanical reporting effects of having more police officers in the streets; i.e, since there are more police officers, more crime is detected. However, we do not find statistically different from zero instantaneous effects for car thefts. This makes sense considering that car thefts are arguably the best measured type of crime. Therefore, this category is less likely to be subject to mechanical reporting effects that could make this instantaneous effect positive.

Finally, we present the instantaneous spillover effects on the right panel of Figure 4. For the four main types of crimes considered, we do not find any spillover effects that are statistically different from zero. This is consistent with our theoretical framework and econometric approach. If the MOs reduce crime in a district and its surroundings via cumulative effects over time, conditional on the cumulative number of MOs and spillover MOs up to week t, one should not observe reductions in crime in places nor evidence of plausible mechanical reporting effects in districts that were not treated.

Figure 4: Instantaneous effects, extensive margin.



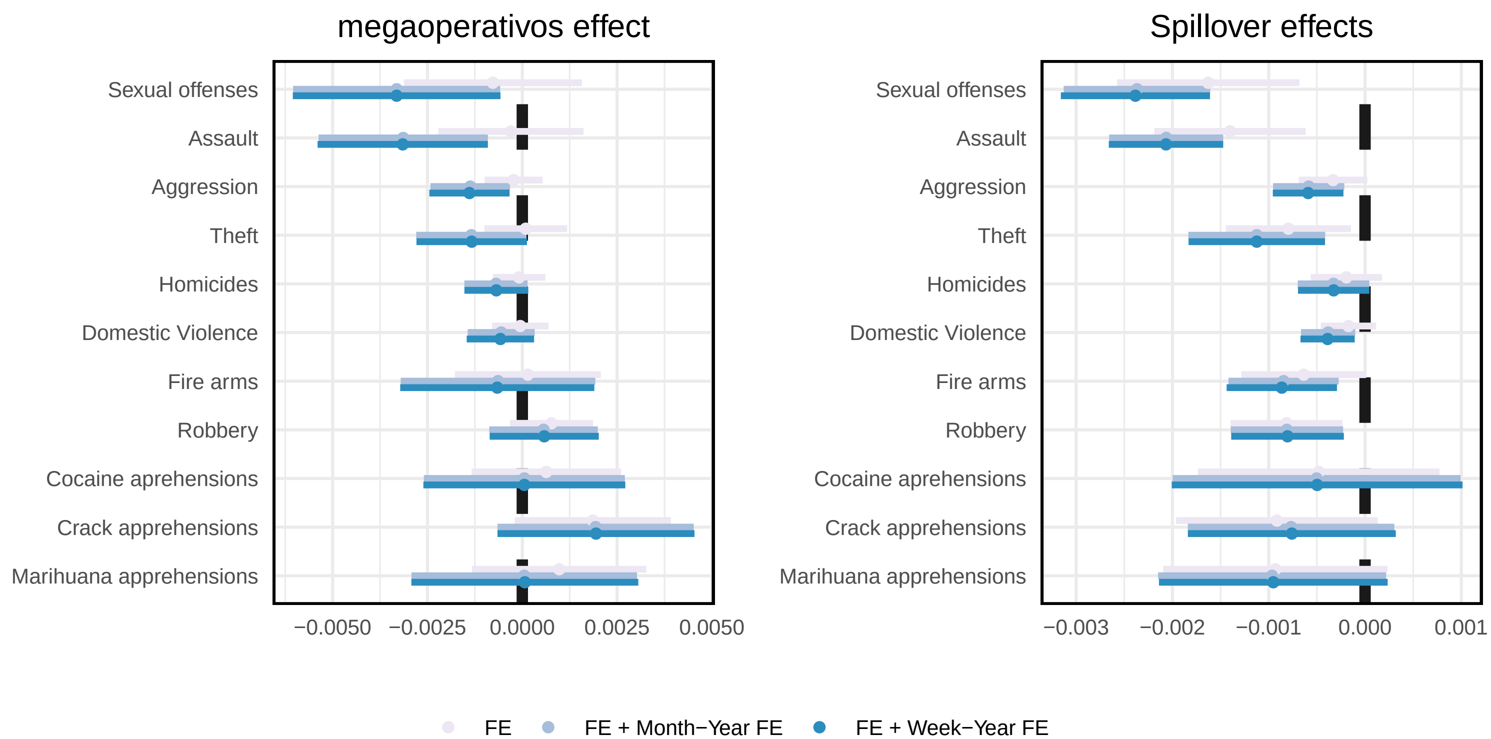
Notes: The left image shows the point estimates for the instantaneous effects executing a megaoperativo along with their 95% confidence intervals. The right image shows the point estimates for the the instantaneous effects of having megaoperativos on crime on districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Results for detailed crimes

Following the same line of reasoning as in the previous subsections, in Figure 5, we show the the cumulative results for the other crimes considered in this work. The MOs had negative cumulative effects on sexual offenses (-2.81%), assaults (-2%), and thefts (-1%, at 10% significance). As for spillover effects, we find negative effects on sexual offenses (-3.1%), assaults (-2.01%), aggressions (-0.77%), thefts (-1.31%), homicides (-0.74, at 10% significance), domestic violence (-0.22%), firearms incidents (-0.75%), and robberies (-0.64%). We do not find any significant cumulative effects for drug apprehensions, but we find negative cumulative spillover effects on the confiscated grams of cocaine (-2.84%) and marijuana (-0.55%).

As for instantaneous effects, for all types of crimes except assaults and thefts, we find no instantaneous effect statistically different from zero. We find negative instantaneous spillover effects on sexual offenses and marijuana apprehensions.

Figure 5: Detailed results, extensive margin



Notes: The left image shows the point estimates for the cumulative effects of an additional megaoperativo along with their 95% confidence intervals. The right image shows the point estimates for the cumulative spillover effect of an additional megaoperativo on crime in districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Robustness checks

This section presents a number of robustness checks.

Intensive margin results

First, we test whether the total length of exposure to an MO -the intensive margin- yields different results from the ones found with the extensive margin. We use the same model specification and find the same conclusions as the ones we found for the extensive margin[6]. We find strong negative MOs cumulative effects for total crimes (-0.98%), violent crimes (-1.6%), and car thefts (-1.37%). As for cumulative spillover effects, the conclusions also mirror the ones that we found with the extensive margin. In particular, our cumulative spillover effects show decreases in total crimes (-1.56%), violent crimes (-2.12%), property crimes (-1.16%), and car thefts (-1.54%). Therefore, when measuring the effects of the MOs via the number of treated hours rather than the number of MOs we find that total crimes are reduced by -2.55%, violent crimes by 3.81%, property crimes by 1.64%, and car thefts by 2.92%.

Mirroring the pattern found with the extensive margin results, we find positive instantaneous MO effect on total crimes, violent crimes, and property crimes, while we find no significant effects on car thefts and, no instantaneous spillover effects on any crime. For the detailed crimes, the intensive margin results also follow the same patterns as in the extensive margin.

Another important feature is that these results are larger than the results found for the extensive margin. On the one hand, this suggests that increasing intensity of treatment by hours per MO rather than the number of MOs might lead to larger decreases in the levels of crime. On the other hand, it shows that no matter how Γ_k is used empirically, we reach the exact same conclusions in terms of relative magnitudes and significance. Nevertheless, to err on the side of caution, we prefer to report the extensive margin results as the main results of this work.

A final result which again mirrors what was found in the extensive margin estimates, is that the cumulative spillover effects are always higher than the cumulative MOs effects. This is also a result that was conjectured in equation (11), thus providing additional empirical support to the theoretical framework of this work.

COVID-19 pandemic

While the MOs create a deterrence effect that accumulates over time, the inhabilitation effect created by the pandemic could have on its own changed the crime dynamics in Costa Rica, thus changing the nature of crime in the economy. Under this scenario, our results could be contaminated by this exogenous shock and we might not be correctly identifying the effects of interest.

To address these concerns, we estimate our model only considering the period from May of 2018 until the end of February 2020. The results are shown in Appendix 32 onwards. We find no cumulative effect from the MOs, but we find very strong spillover effects. In particular we find that via spillover effects total crimes are reduced by -0.9%, violent crimes by -0.82%, property crimes by -0.98%, and car thefts by -0.93%. For these crimes, we find that the instantaneous MO and spillover effects are statistically no different from zero.

[6] Please see Appendices 26 to 31 for the figures displaying the results described in this subsection.

Similarly, we find no cumulative MOs effect for the other types of crimes. There are negative spillover effects for sexual offenses (-2.10%), assaults (-0.83%), and aggressions (-0.92%). We also don´t find any instantaneous nor spillover effects for any crime.

These are results that can be understood with our theoretical framework. Equation (11) stated that the cumulative spillover effects are expected to be larger than the the cumulative MOs effect because of the multiplicative spillover effect. This is, cumulative spillover effects are larger because they are affected by more MOs via the change they create in the probability of getting caught p_k. This is something to be expected given the nature of spillovers. During the pre-pandemic period (May 2018 to February 2020), the average number of treated districts surrounding a spillover district is 4.43 while the average number of MOs is 2.90. Therefore, spillover districts are accumulate more treatment thatn non-spillover districts.

To test the hypothesis of the in-time conjecture of equation (11) we estimate our econometric model but we add one more week of data at a time. This allows us to determine whether or not significant cumulative spillover effects precede the direct cummulative effects of MOs. We present the plot of the cumulative results in Appendix 44 from May 2019 onward. Before this, the coefficients of these regressions are unstable and erratic, most likely reflecting problems with small treatment length in the data. The cumulative MO effect starts a decreasing trend in magnitude at the beginning of 2020, and this trend further precipitates during the pandemic. Then, the coefficients seem to reach a new stationary state at the beginning of 2021. At first glance, this would indicate our previous cumulative MO negative effects were due to the inhabilitation effects of COVID-19 rather than to deterrence effects from the MOs.

However, the cumulative spillover effects for total crimes, violent crimes, and car thefts has been negative and statistically significant since November of 2019. In tandem, the cumulative MO and spillover week by week results are evidence of the second conjecture of equation (11). We should expect to see cumulative spillover effects before MO effects because the intensity of treatment -whether it is on the intensive or the extensive margin- is higher for spillover districts than for treated districts. Hence, although it cannot be directly proven directly that the MOs would have continued their decreasing trend in magnitude -crime reducing results-, its relative behavior with the spillover effects conforms to the theoretical framework we have presented here. Furthermore, the instantaneous effects show behavior consistent with previous results: positive instantaneous MO effects for total crimes, violent crime, and property crimes, and not significant results for car thefts. Also, the spillover effects are not statistically different from zero.

Anticipation effects

An important concern for identification is that criminals could be anticipating the policy and reacting according to these expectations about the future. In such a case, our estimates would not be accurately identifying the effects of interest since treatment variables are correlated with the error via future observations. To address this concern, we estimate our workhorse model in equation (12) and add leads of the instantaneous MO and spillover effects. If there are no anticipation effects, we would expect these lead variables to not be statistically different from zero, while our cumulative results would remain unchanged.

Table 2: Leads test

	Dependent variable:			
	Total crimes	Violent	Property	Car theft
	(1)	(2)	(3)	(4)
CumMO	-0.010^{***}	-0.010^{***}	0.0001	-0.001^{***}
	(0.003)	(0.003)	(0.001)	(0.0003)
CumSpillover	-0.008^{***}	-0.006^{***}	-0.002^{***}	-0.001^{***}
	(0.001)	(0.001)	(0.0005)	(0.0001)
Lead MO	0.113	0.104	0.010	0.011
	(0.088)	(0.068)	(0.034)	(0.016)
MO	0.220^{*}	0.177^{*}	0.044	-0.0004
	(0.123)	(0.099)	(0.044)	(0.020)
Lead spillover	0.089	0.029	0.059	0.019
	(0.072)	(0.055)	(0.039)	(0.017)
Spillover	0.064	0.025	0.039	0.005
	(0.081)	(0.065)	(0.041)	(0.017)
District FE	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes
Observations	25,046	25,046	25,046	25,046

Notes: The table shows the coefficient estimates of a regression that adds the lead of the megaoperativo and spillover dummy variables. *p<0.1; **p<0.05; ***p<0.01.

The results in Table 2 show that the inclusion of the leads does not change our previous results. Both leads are statistically insignificant for all crimes, and we still find cumulative MO results for total crimes, violent crimes, and car thefts. We also find negative cumulative spillover effects for all crimes. In Appendices 46 and 47, we show the results for the rest of the crimes used in this work and reach the same conclusions.

In addition, this result conforms with our theoretical framework. In our model, by not modeling the expectations of the agent, we were implicitly assuming no anticipation effects. The results in this subsection provide further evidence that the model presented in this work rationalizes the results of the policy under study.

Conclusion and discussion

In this work, we study the effect of the megaoperativos security policy in San José, Costa Rica. This compromises large police interventions that have been implemented all over the country since May 2018, and constitute the country's most significant effort at tackling crime in recent years.

We find robust and significant evidence that the policy decreased crime via its cumulative effects. In particular our results indicate that MOs via direct and spillover effects on average reduced total crimes by 2.35%, violent crimes by 3.67%, property crimes by 1.03%, car thefts by 2.15%, sexual offenses by 5.92%, assaults by 4.01%, aggressions by 1.95%, and thefts by 2.32%. That is, over time the reductions in crime are due to effects of regular treatment that also varied in intensity. These cumulative effects present themselves via direct effects on the districts that were treated but also via cumulative spillover effects over time and space. The amount of treatment and its intensity have persistent effects on the levels of crime in the economy. Along similar lines, we also investigated the effect of the policy via the intensive margin -total hours accumulated- rather than via the extensive margin -number of MOs- and we reach the same conclusions. This implies that it does not matter how this type of policy is implemented; what matters is its continuous application and intensity accumulation over time.

Besides the empirical results, we also contribute to the literature byproposing a theoretical model that models the MO policy as a macroeconomic variable. The amount of police officers, the state of the economy and the total crime in the economy affect the decision of a representative agent to commit or not commit crime via changes in the probability of committing crime. Within this model, the probability of getting caught is a dynamic problem that accumulates previous history. The model generates predictions that we were able to prove empirically with our data. One of these predictions is that the cumulative spillover effects are larger than the direct effect of the MOs. This implies that the intensity of treatment due to be surrounded by units that are treated has a larger effect than the effect of being a district with more police officers. This finding has important public policy implications: crime hot spots can be affected over time via in-time and geographic spillovers. Hence, police and security resources can be reallocated based on this rule and strengthen the outcomes of these types of policies.

The theoretical model also helps justify the validity of our empirical approach and explain the impact of the COVID-19 pandemic. The pandemic constituted an inhabilitation effect on the economy. It could also have changed the the production function of crime or the preferences of criminals. When we consider only the data before the pandemic, we find no cumulative effects from the MOs, but there are strong cumulative spillover effects. At first glance, this would suggest that our previous results are mostly driven by the pandemic inhabilitation effect. However, upon closer inspection, we find that the dynamics of the results and the fact that the significance and the relative larger magnitude of the spillover effects conform to the theoretical prediction of our model. Therefore, it is more likely that prior to the pandemic, enough time periods had passed for the MOs cumulative effect to become as significant as the cumulative spillover effects.

The theoretical model also justifies our econometric approach to measuring the effect of the MOs. Conditional on the cumulative number of MOs and spillovers, one should not see effects in the immediate term (what we call instantaneous effects) if the policy works via cumulative effects. Furthermore, this distinction between cumulative and instantaneous effects allows us to account for the increases in crime that one might see in the data due to mechanical reporting effects. That is, more crime is reported because there are more police officers in the street. Thanks to the panel dataset structure used in this work, we can isolate this effect and separate it from the cumulative effects that the policy is expected to have. Furthermore, the panel dataset allows us to control for time trends and intrinsic geographic characteristics that might affect crime in the economy.

With respect to previous literature, our study corroborates the finding that hot spots policies can have decreasing effects on crime. Nonetheless, we find very strong and significant spillover effects. Further, we find that these spillovers work in time and in geography, thus implying that hot spots policies can generate positive security externalities that can be sustained over time and space. We propose two plausibles reasons for our spillover effects findings with respect to previous literature. First, by using a panel dataset we can wait for these spillover effects to manifest over time. Previous literature may not have found spillover effects simply because they did not give time for the policy to manifest. Both our estimates and our theoretical framework predict that these effects take time to manifest and linger. By using cross-sectional data one might not be able to observe these spillover effects. On the other hand, we see the spillover effects over districts rather than blocks, areas of a city or streets. This gives enough distance for economic agents to reallocate. In other words, previous studies may not have given "enough physical space" for potential criminals to react. This previous limitation might be a reason why spillovers are not always found in other studies.

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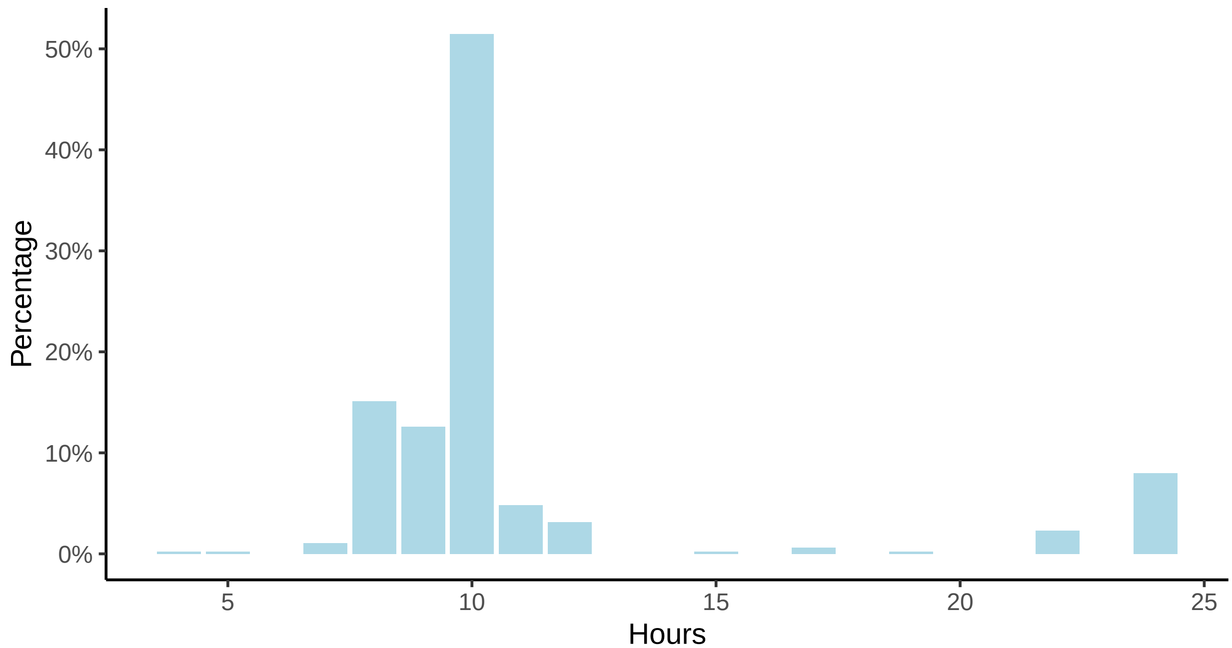
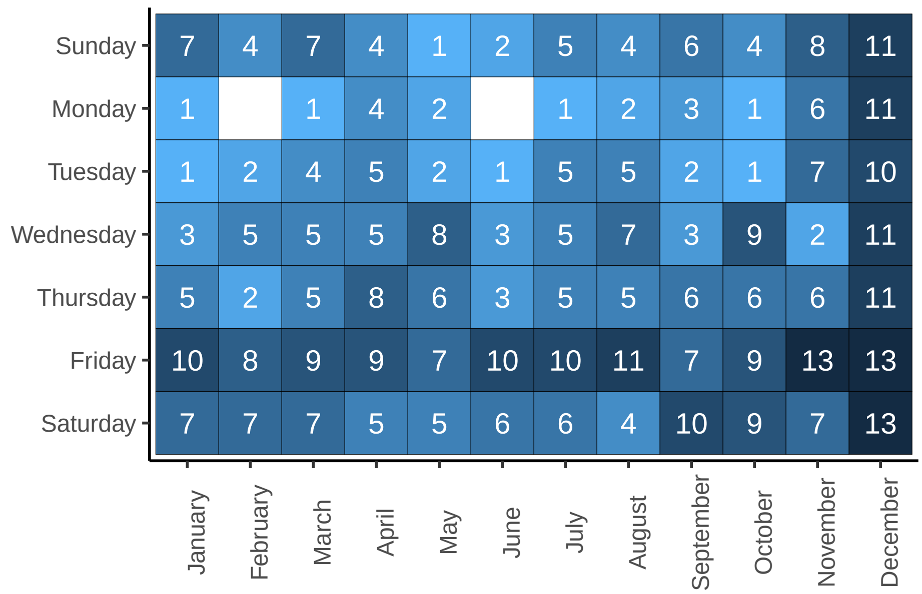
Figure A1: Duration of megaoperativos, 2018-2022



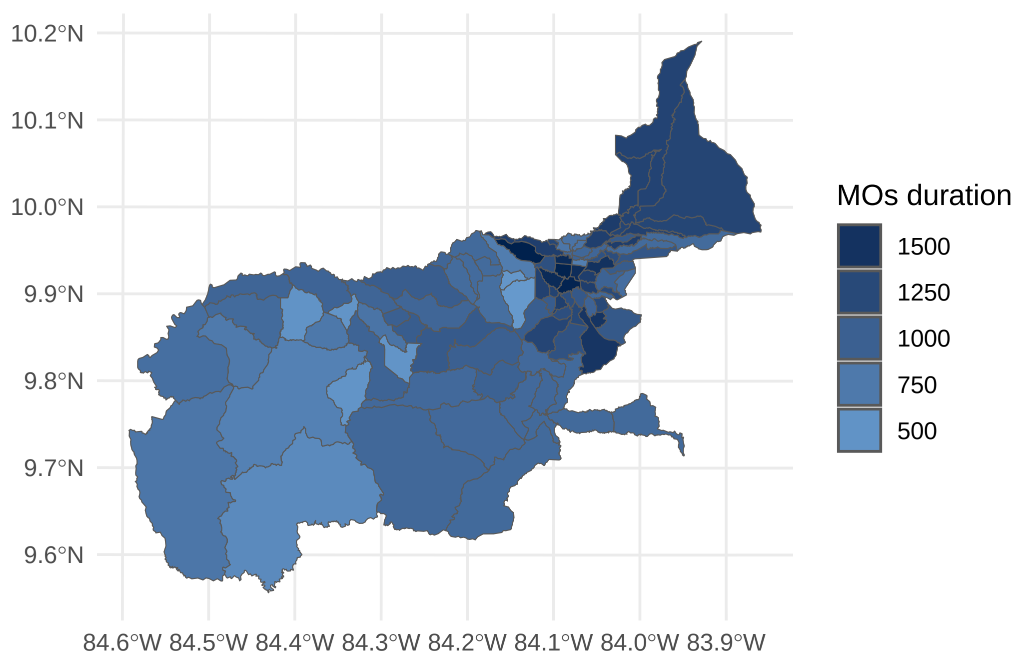
Notes: the figure shows how the number of megaoperativos are disributed by their lenght of terms of hours. Over 70% of megaoperativos lasted at least 10 hours.

Figure A2: megaoperativos by month and day, 2018-2022



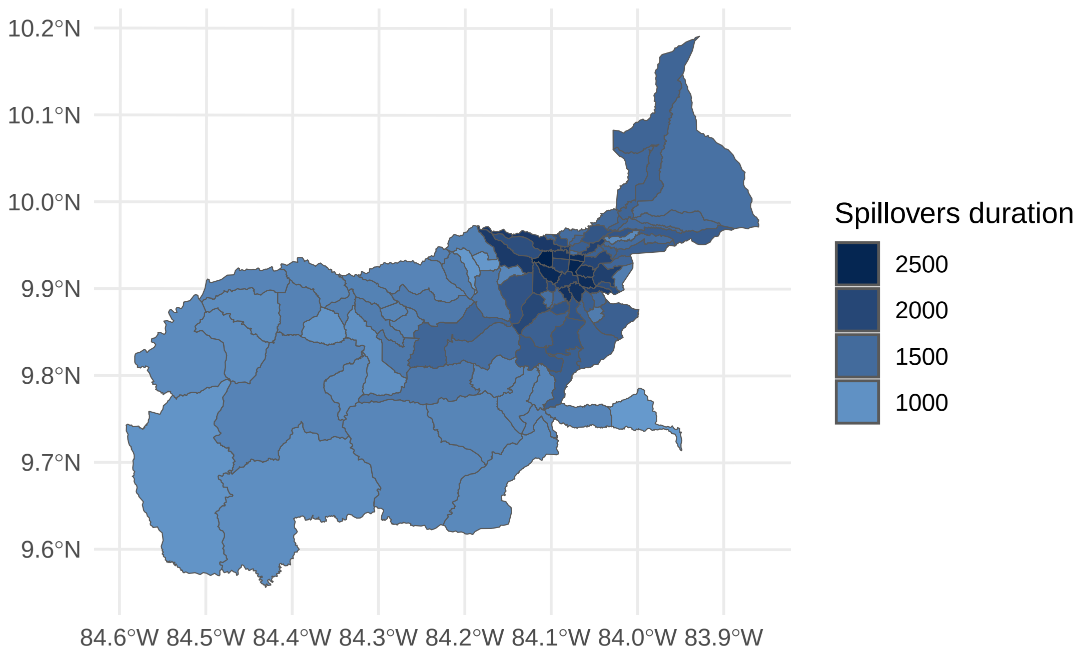
Notes: the figure shows the distribution of MOs over days of the week and month over the 2018-2021 period. megaoperativos are mostly concentrated at the end of the week and the end of the year.

Figure A3: Duration of megaoperativos per district in hours, 2018-2022



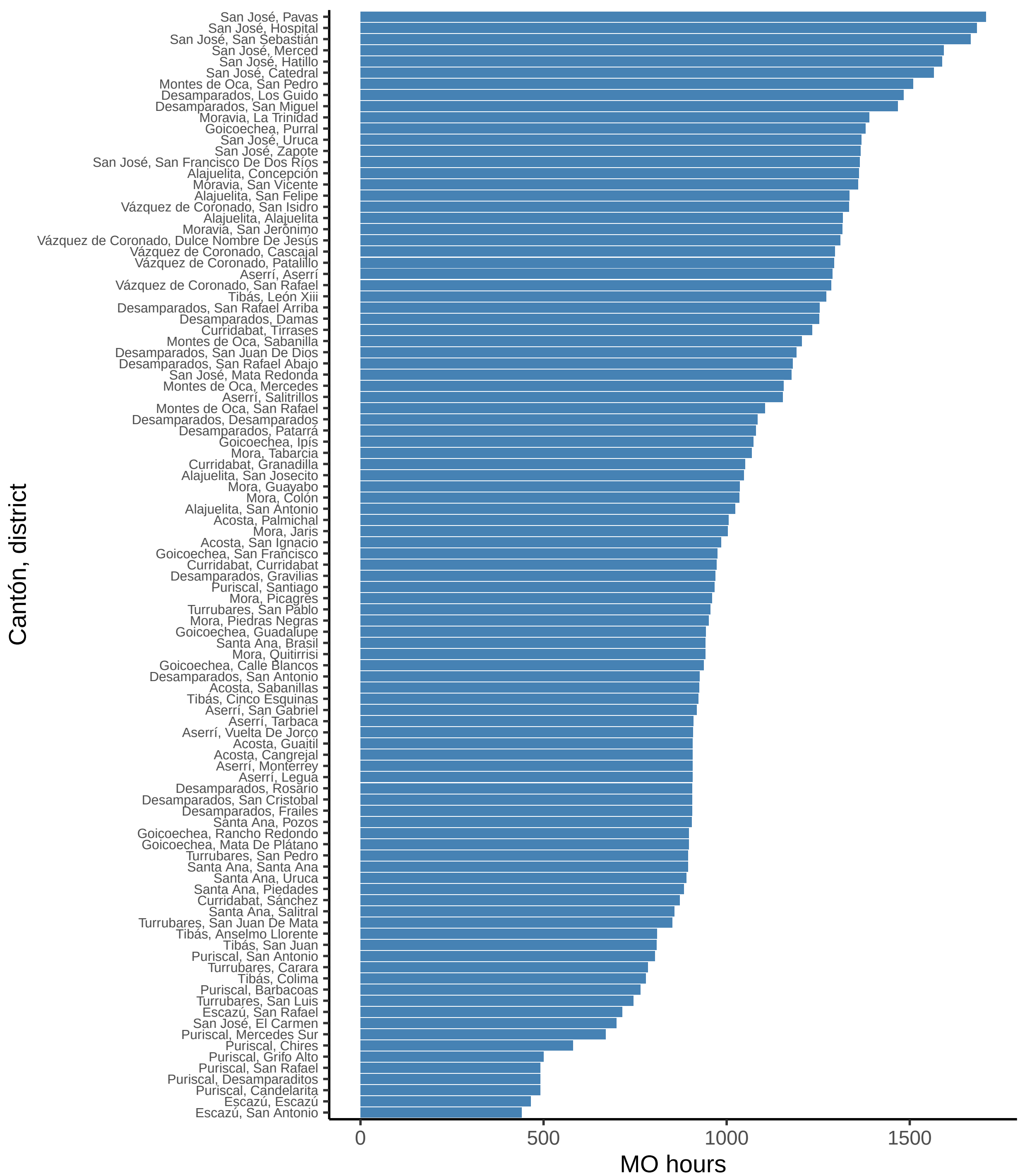
Notes: the map shows the total hours megaoperativos were executed by district from May of 2018 until December of 2022.

Figure A4: Duration of megaoperativos spillovers per district in hours, 2018-2022



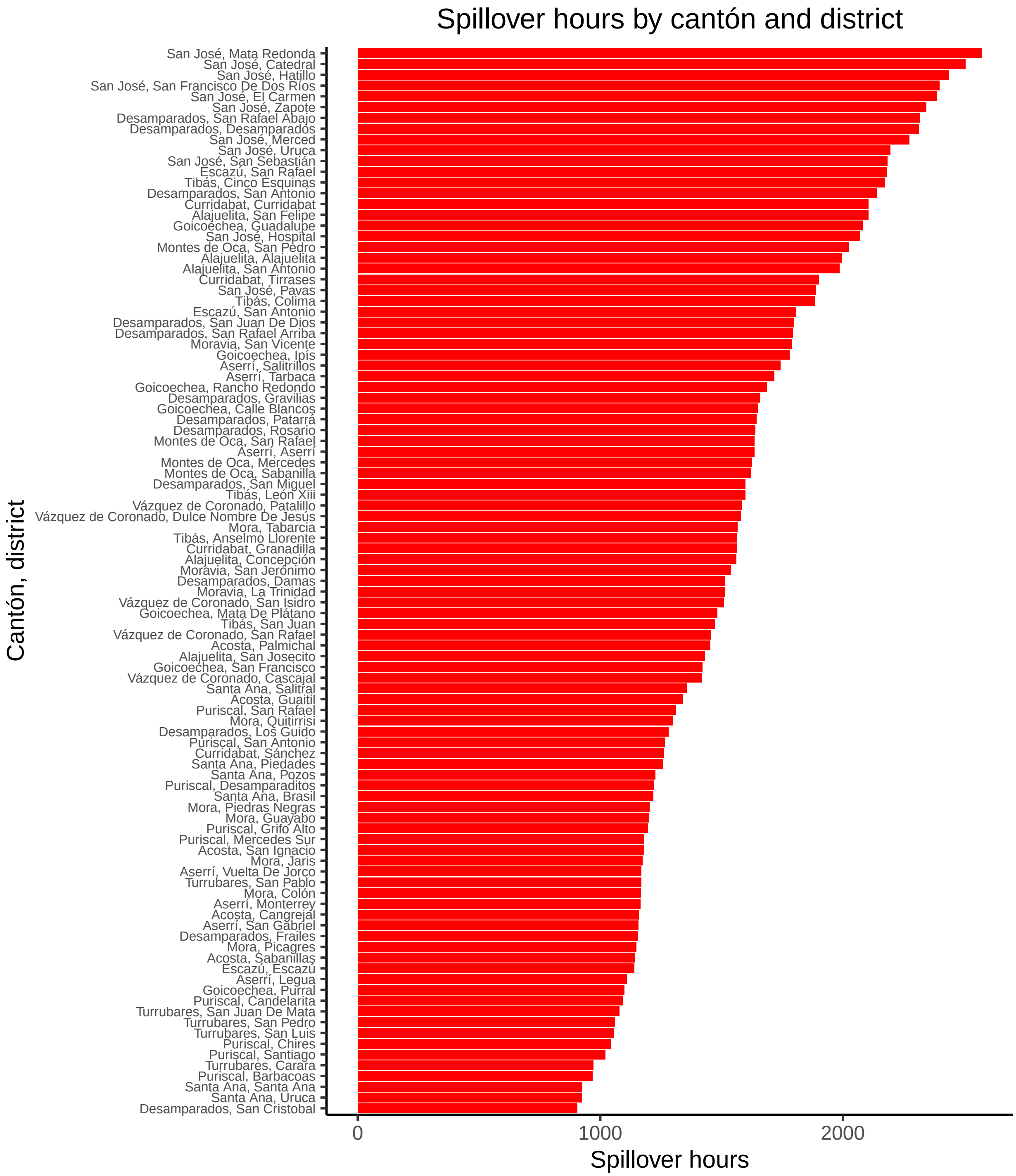
Notes: the map shows the total number of hours megaoperativos were executed in a surrounding district for each district from May of 2018 until December of 2022.

Figure A5: Megaoperativo hours by cantón and district, 2018-2022



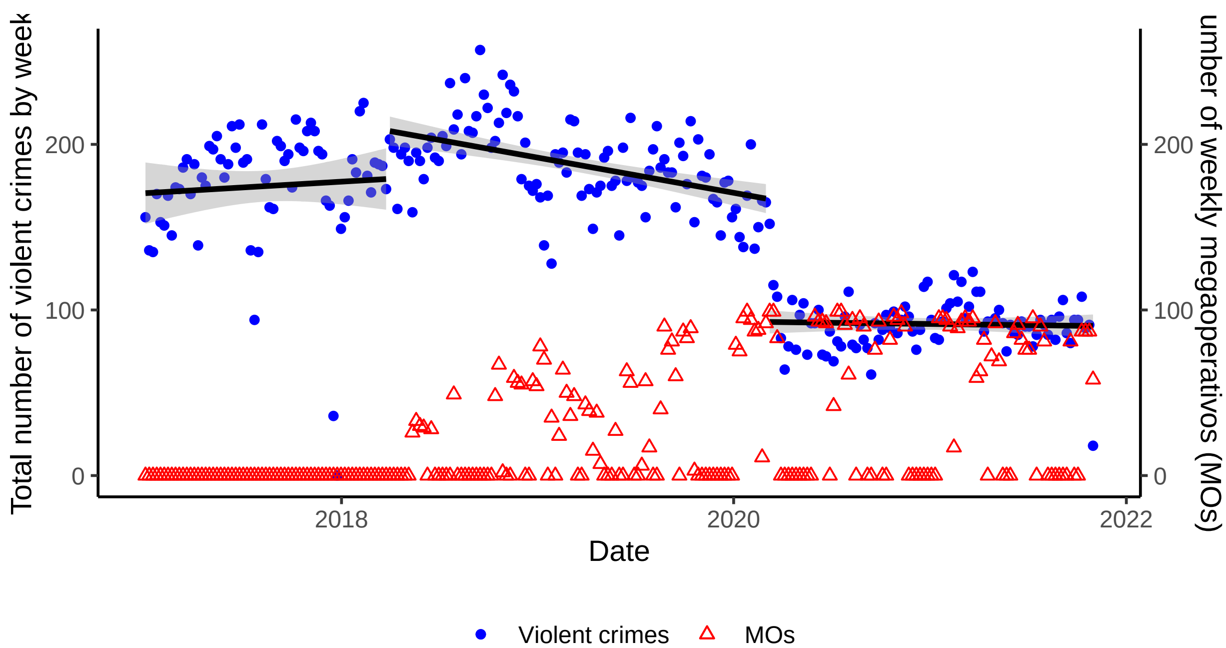
Notes: the image shows the total hours of megaoperativos for each district from May of 2018 until December of 2022.

Figure A6: Spillover hours by cantón and district, 2018-2022



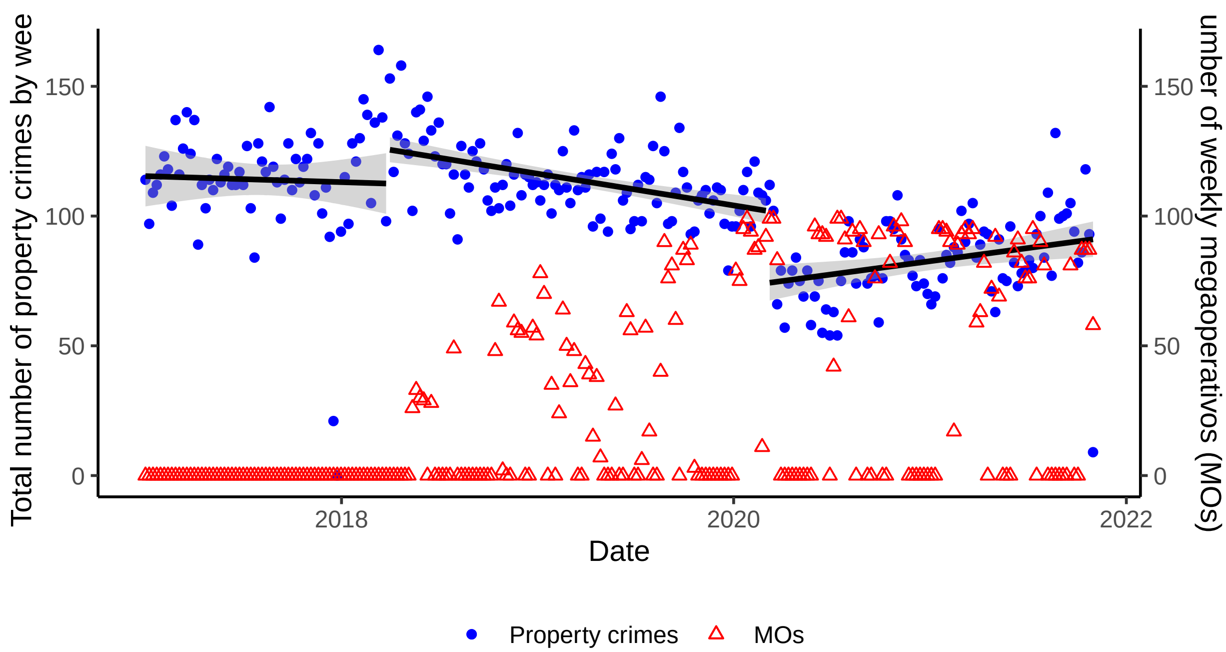
Notes: the image shows the total hours that surrounding districts were treated with megaoperativos for each district from May of 2018 until December of 2021.

Figure A7: megaoperativos and total violent crimes by week



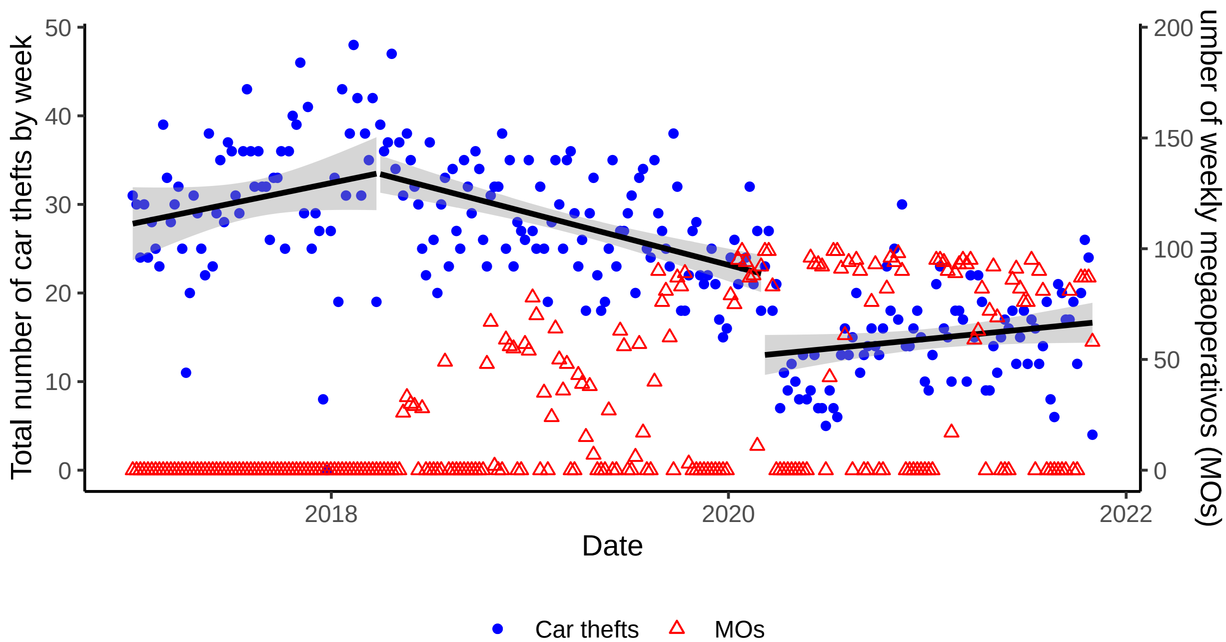
Notes: Plot shows the total number of violent crimes in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of violent crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A8: megaoperativos and total property crimes by week



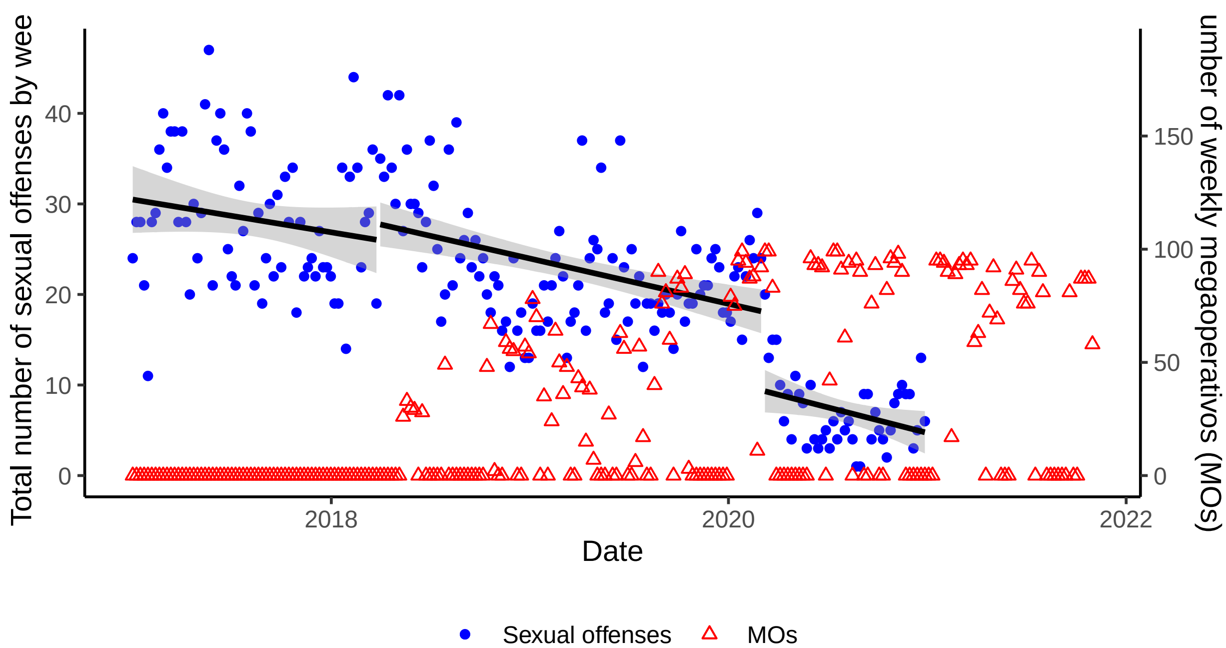
Notes: Plot shows the total number of property crimes in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of property crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A9: megaoperativos and car thefts by week



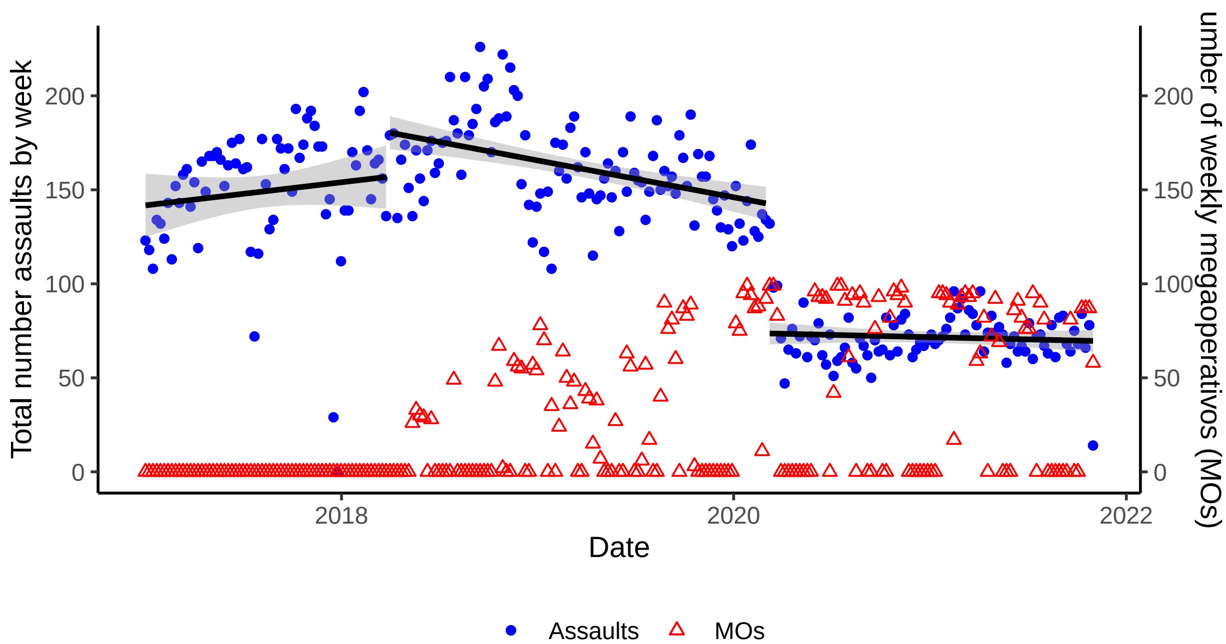
Notes: Plot shows the total number of car thefts in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of car thefts during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A10: megaoperativos and sexual offenses by week



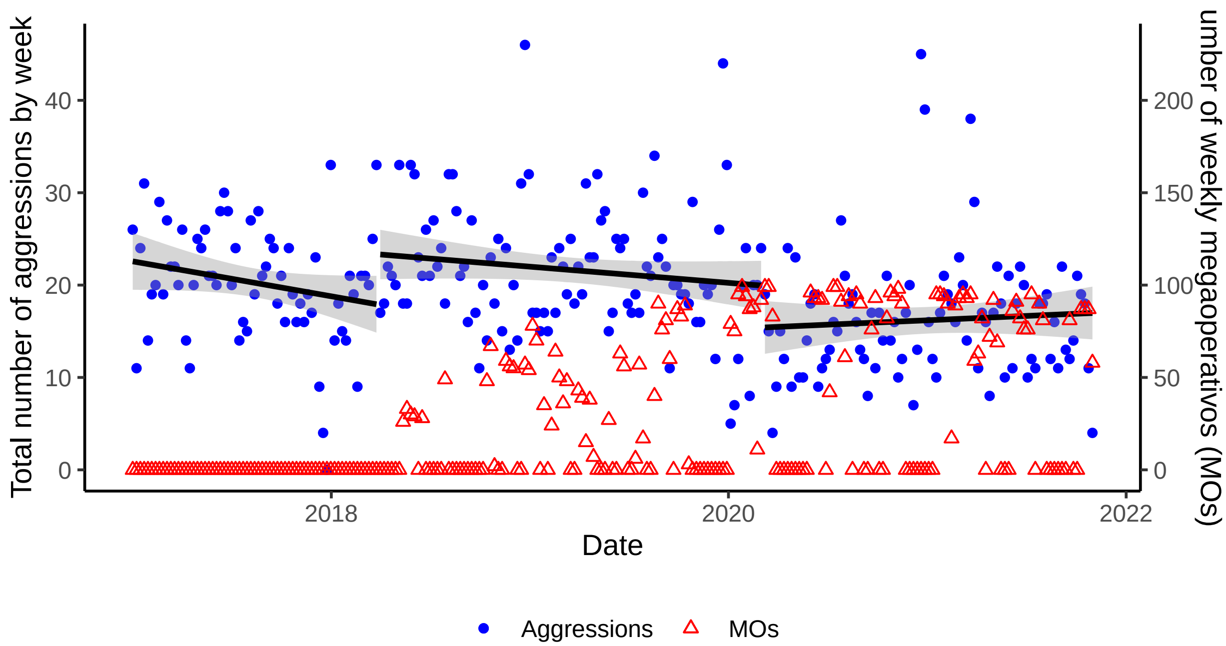
Notes: Plot shows the total number of sexual offenses in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A11: megaoperativos and assaults by week



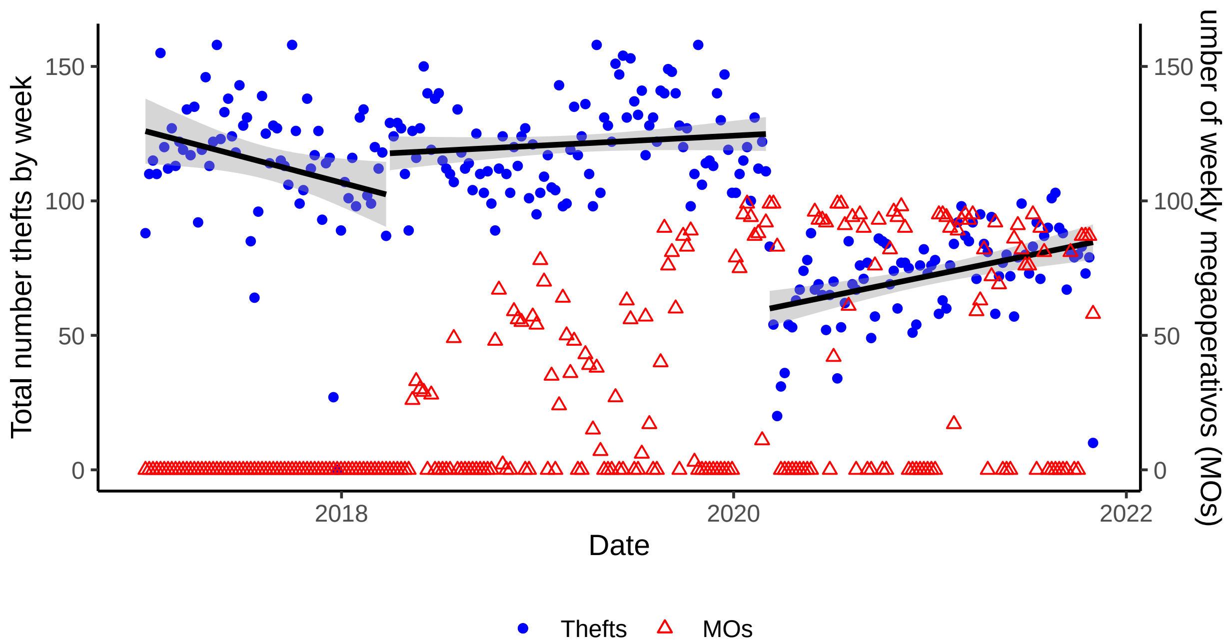
Notes: Plot shows the total number of assaults in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A12: megaoperativos and aggressions by week



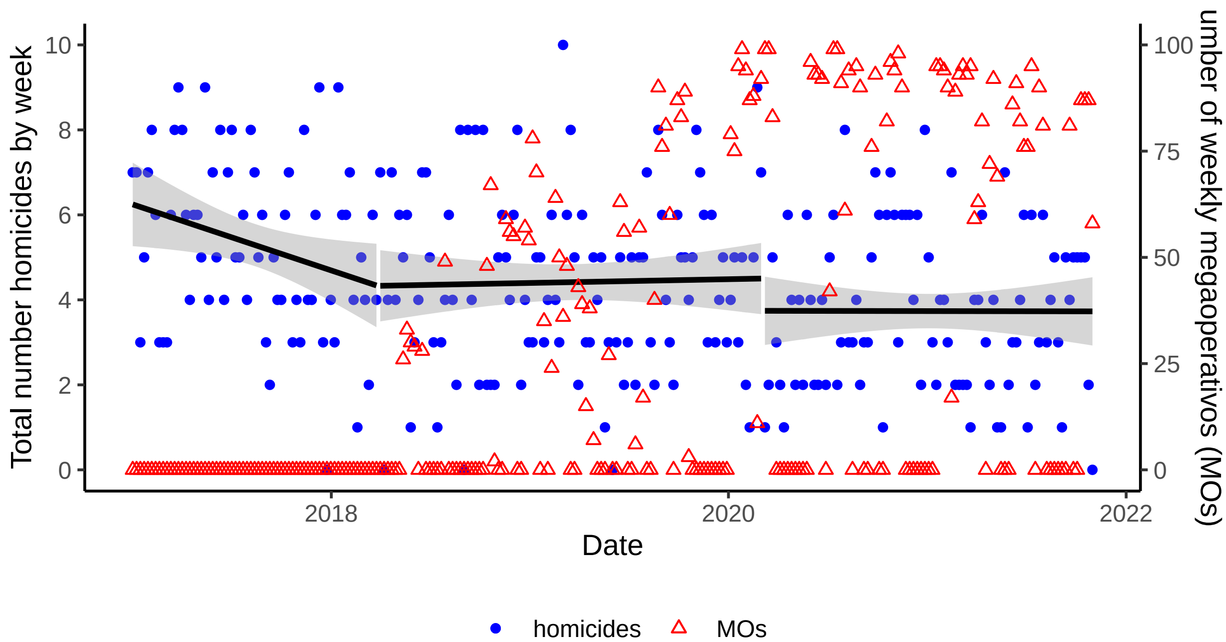
Notes: Plot shows the total number of aggressions in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A13: megaoperativos and thefts by week



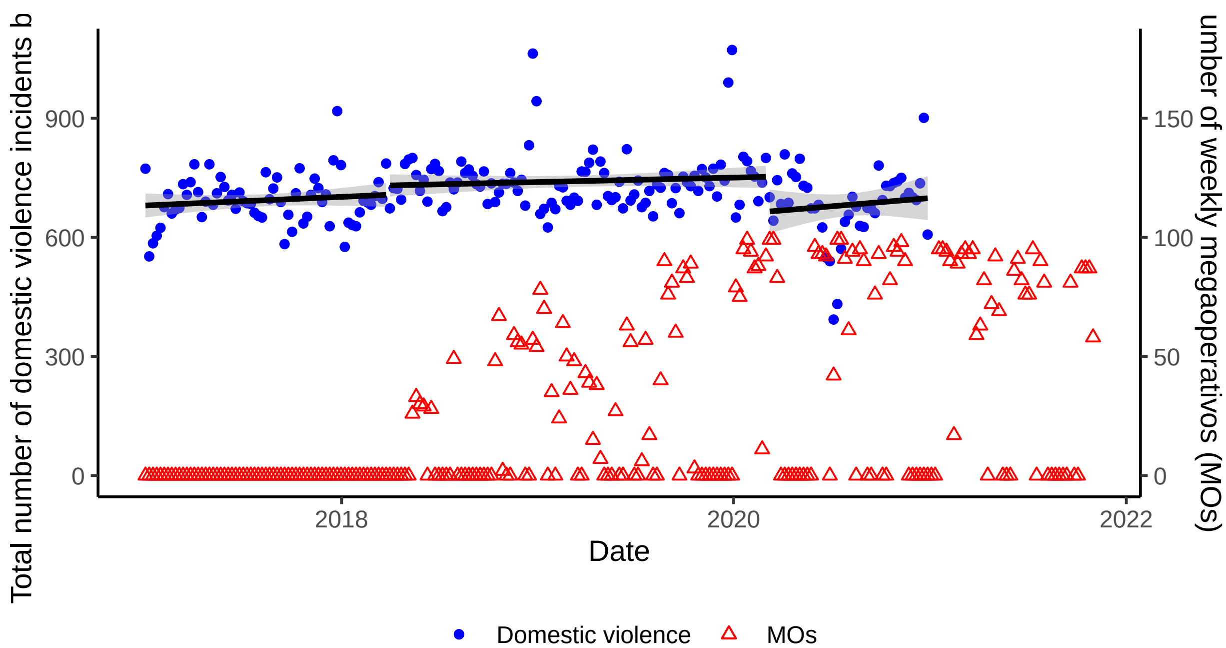
Notes: Plot shows the total number of thefts in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of thefts during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A14: megaoperativos and homicides by week



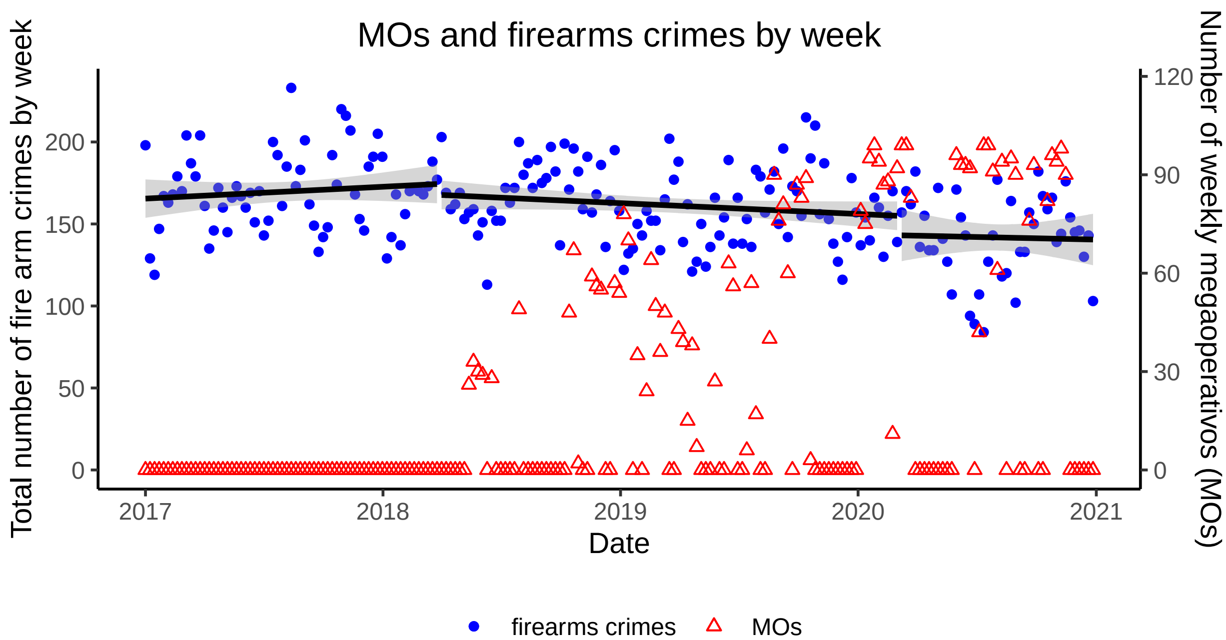
Notes: Plot shows the total number of thefts in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of thefts during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A15: megaoperativos and domestic violence incidents by week



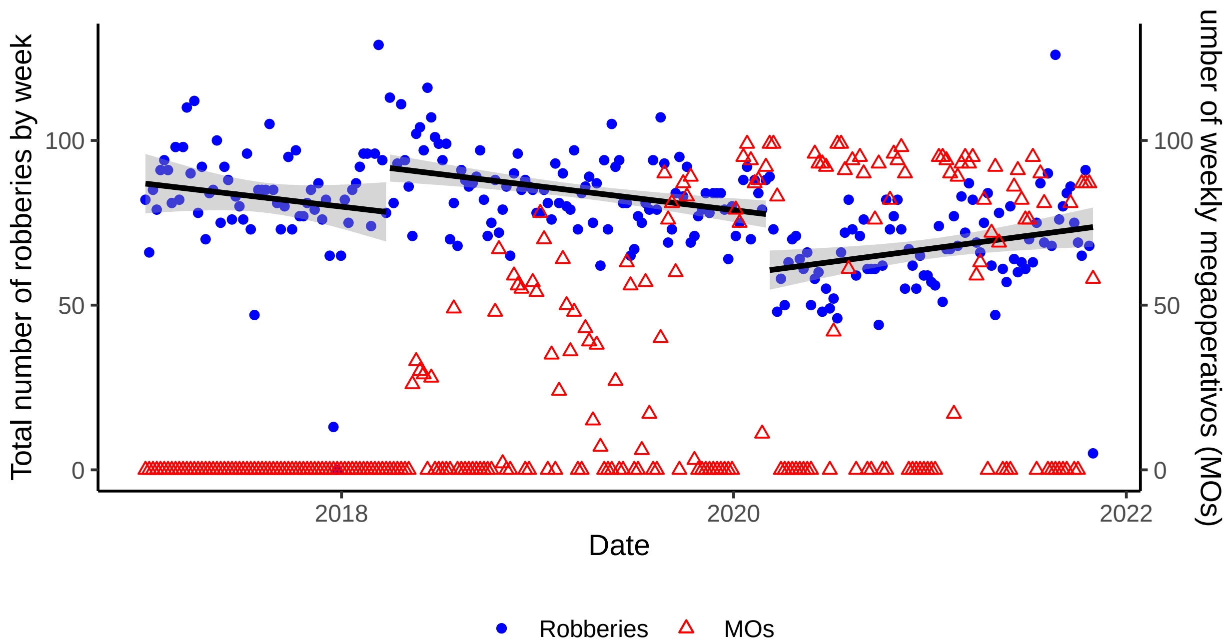
Notes: Plot shows the total number of domestic violence incidents in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of firearms crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A16: megaoperativos and firearms crimes by week



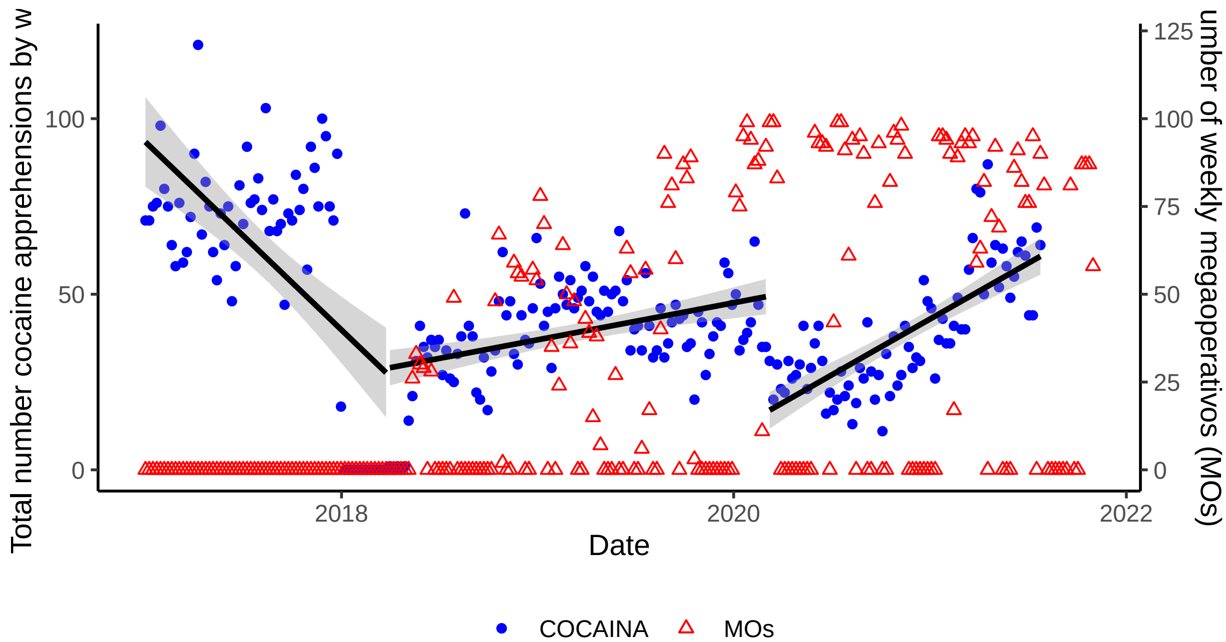
Notes: Plot shows the total number of firearms crimes in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of firearms crimes during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A17: megaoperativos and robberies by week



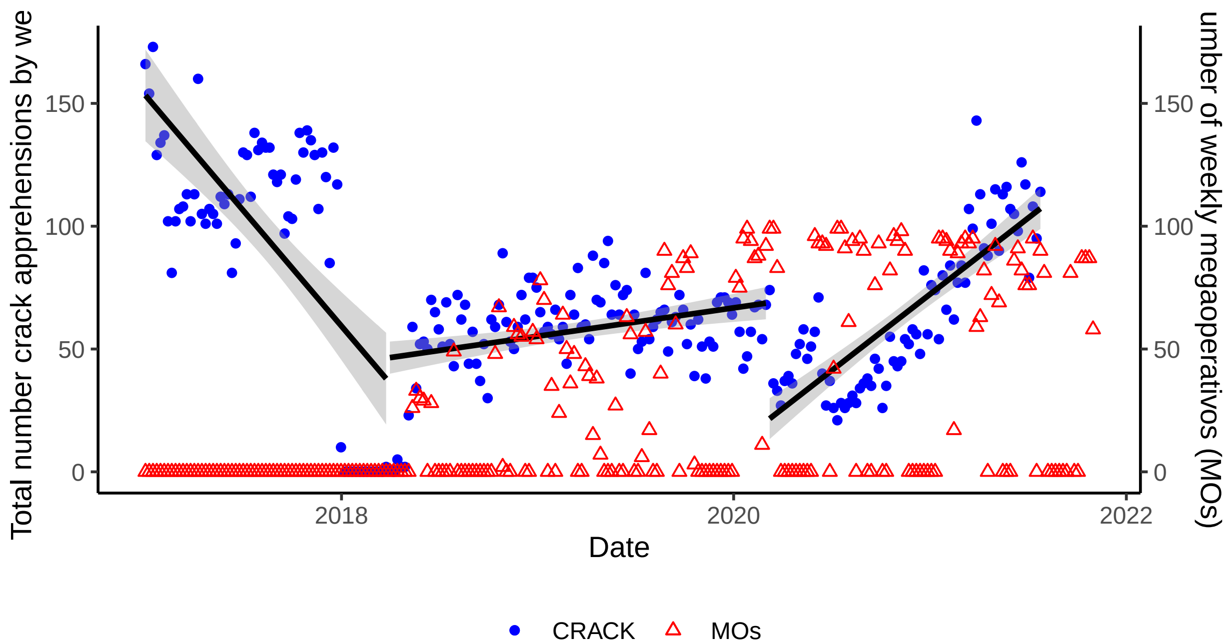
Notes: Plot shows the total number of robberies in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of robberies during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A18: megaoperativos and cocaine apprehensions by week



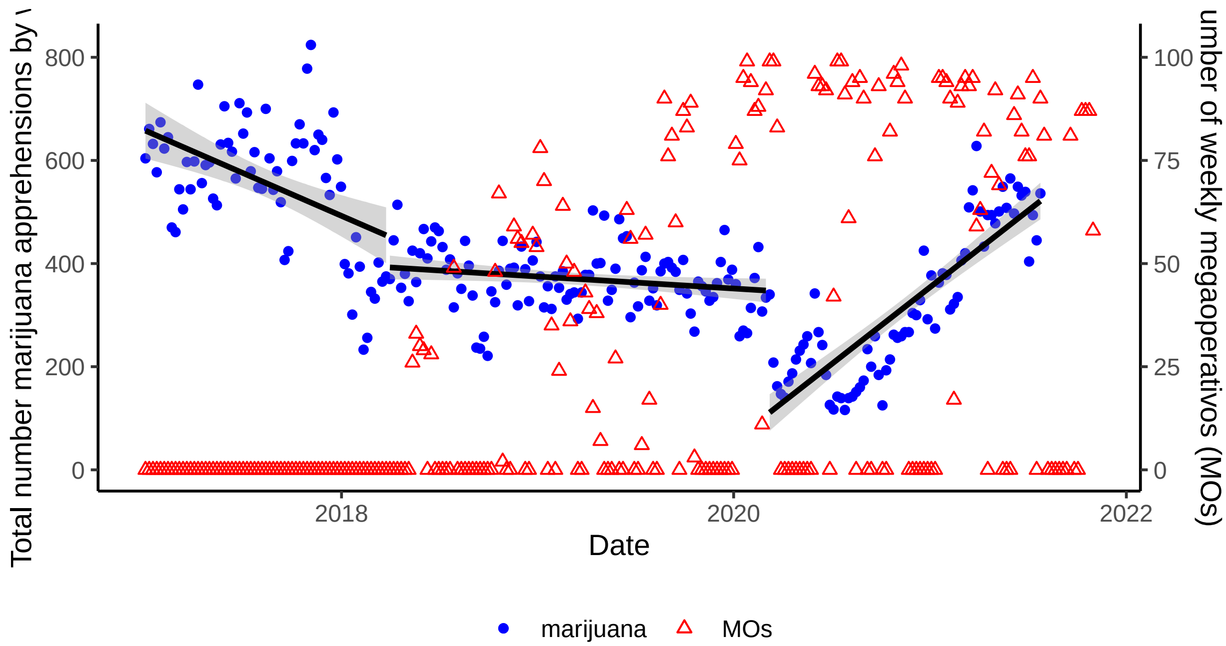
Notes: Plot shows the total number of robberies in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of robberies during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A19: megaoperativos and crack apprehensions by week



Notes: Plot shows the total number of robberies in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of robberies during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Figure A20: megaoperativos and marijuana apprehensions by week



Notes: Plot shows the total number of robberies in solid circles and the number of megaoperativos per week are shown in hollow triangles for 2016-2022. The regression lines depict the relationship between time and the total number of robberies during three distinct periods: pre-MOs (January 2017-April 2018), pre-pandemic (May 2018-February 2020) and during the pandemic onward (March 2020-December 2021).

Appendix 21: Pre-trend period estimates, detailed crimes, 2017-2018

	No controls estimates						
	Sexual offenses	Assault	Aggression	Theft	firearms	Robbery	Domestic Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre-trend	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00001^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
District FE	No	No	No	No	No	No	No
Year-week FE	No	No	No	No	No	No	No
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247
	Fully controlled estimates						
	Sexual offenses	Assault	Aggression	Theft	firearms	Robbery	Domestic Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pre-trend	0.00000	0.00001	-0.00000	-0.00002	0.00001	-0.00001^{*}	-0.00000
	(0.00000)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00002)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,247	5,247	5,247	5,247	5,247	5,247	5,247

Note: *p<0.1; **p<0.05; ***p<0.01

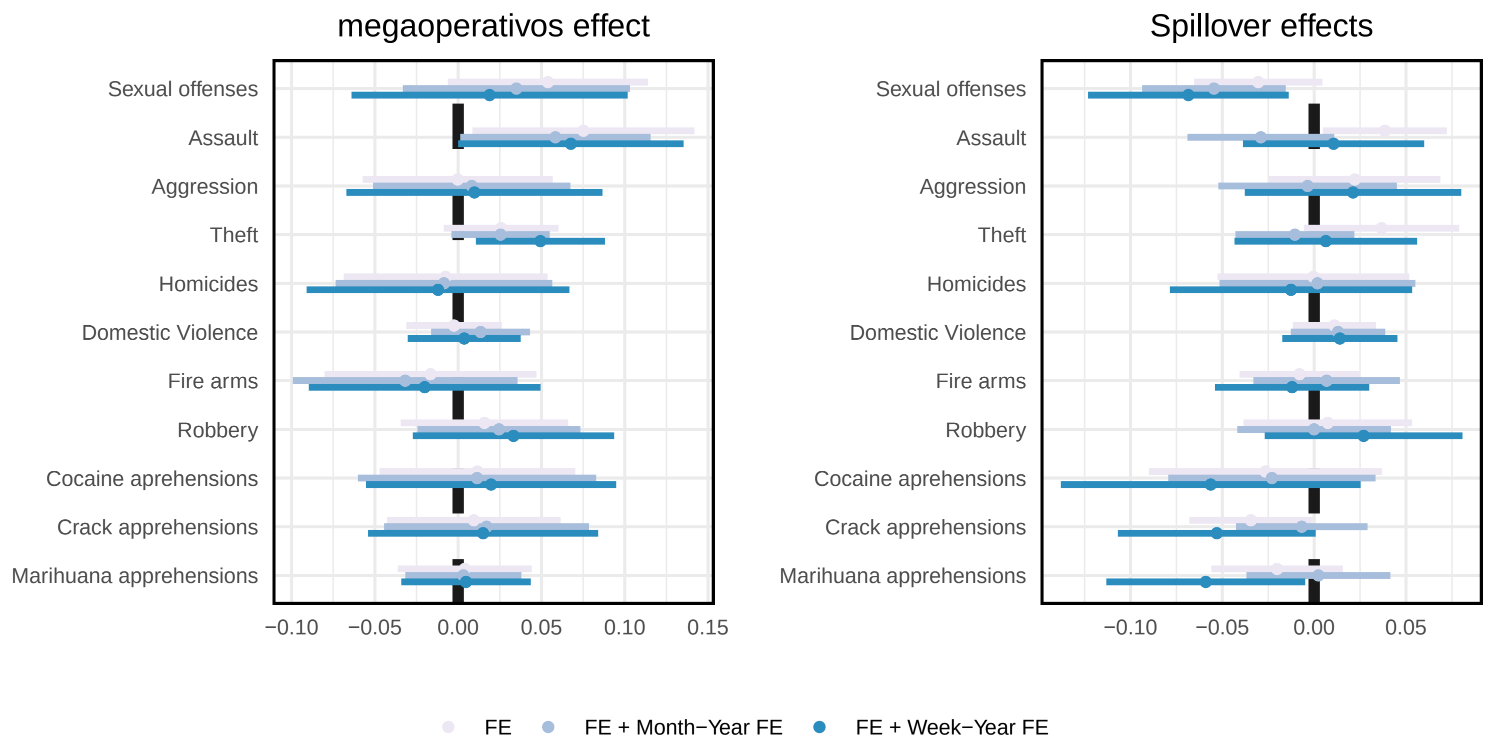
Appendix 22: Pre-trend period estimates, drug crimes, 2017-2018

	No controls estimates					
	Cocaine	Crack	marijuana	Cocaine grams	Crack grams	marijuana grams
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-trend	-0.00000^{***}	-0.00000^{***}	-0.00001^{***}	-0.00001^{*}	-0.00004^{*}	-0.0001
	(0.00000)	(0.00000)	(0.00000)	(0.00001)	(0.00002)	(0.0001)
District FE	No	No	No	No	No	No
Year-week FE	No	No	No	No	No	No
Observations	5,247	5,247	5,247	5,247	5,247	5,247

	Fully controlled estimates					
	Cocaine	Crack	marijuana	Cocaine grams	Crack grams	marijuana grams
	(1)	(2)	(3)	(4)	(5)	(6)
Pre-trend	0.00000	-0.00003	-0.00000	-0.0002	-0.001	0.0003
	(0.00001)	(0.00002)	(0.00004)	(0.0003)	(0.001)	(0.001)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,247	5,247	5,247	5,247	5,247	5,247

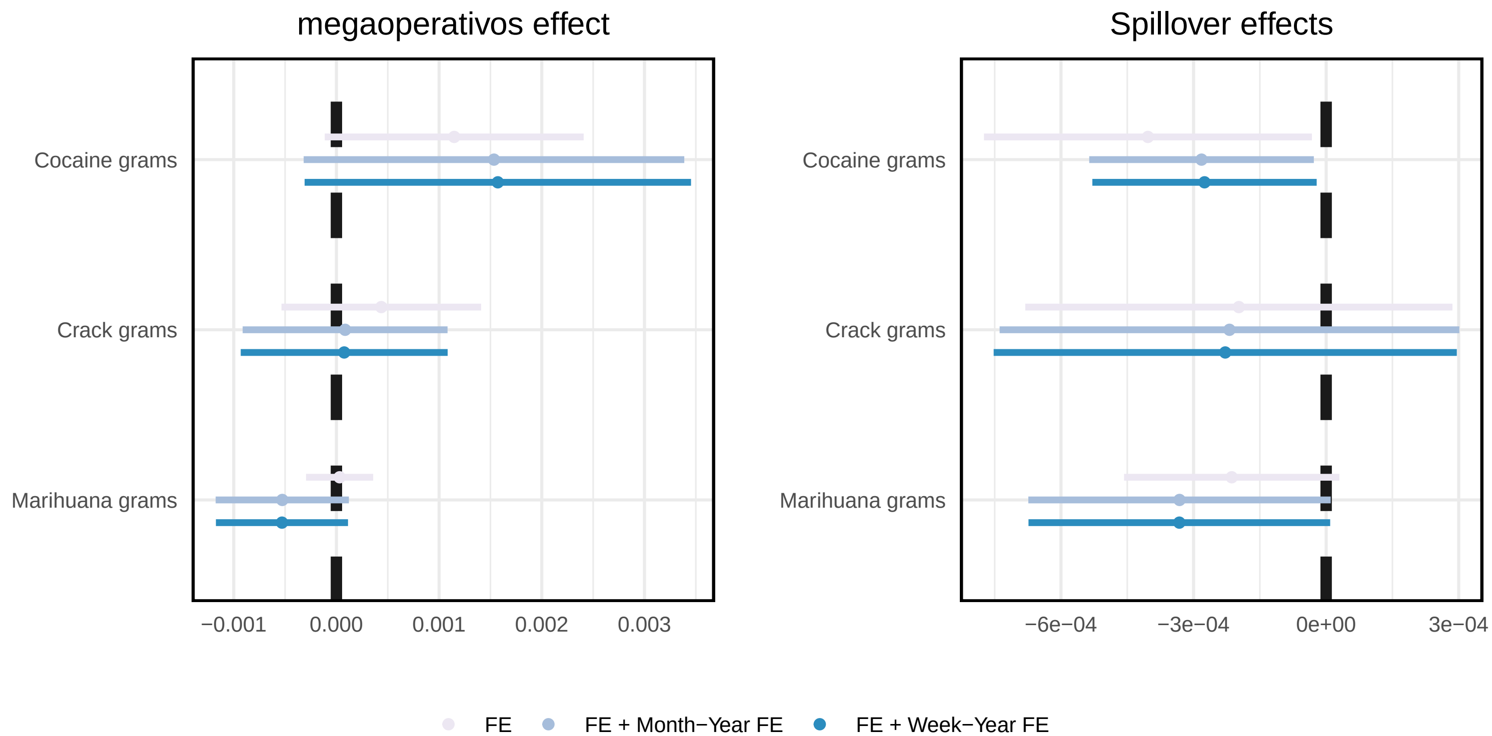
Note: *p$<$0.1; **p$<$0.05; ***p$<$0.01

Figure A23: Instantaneous effects, detailed crimes, extensive margin.



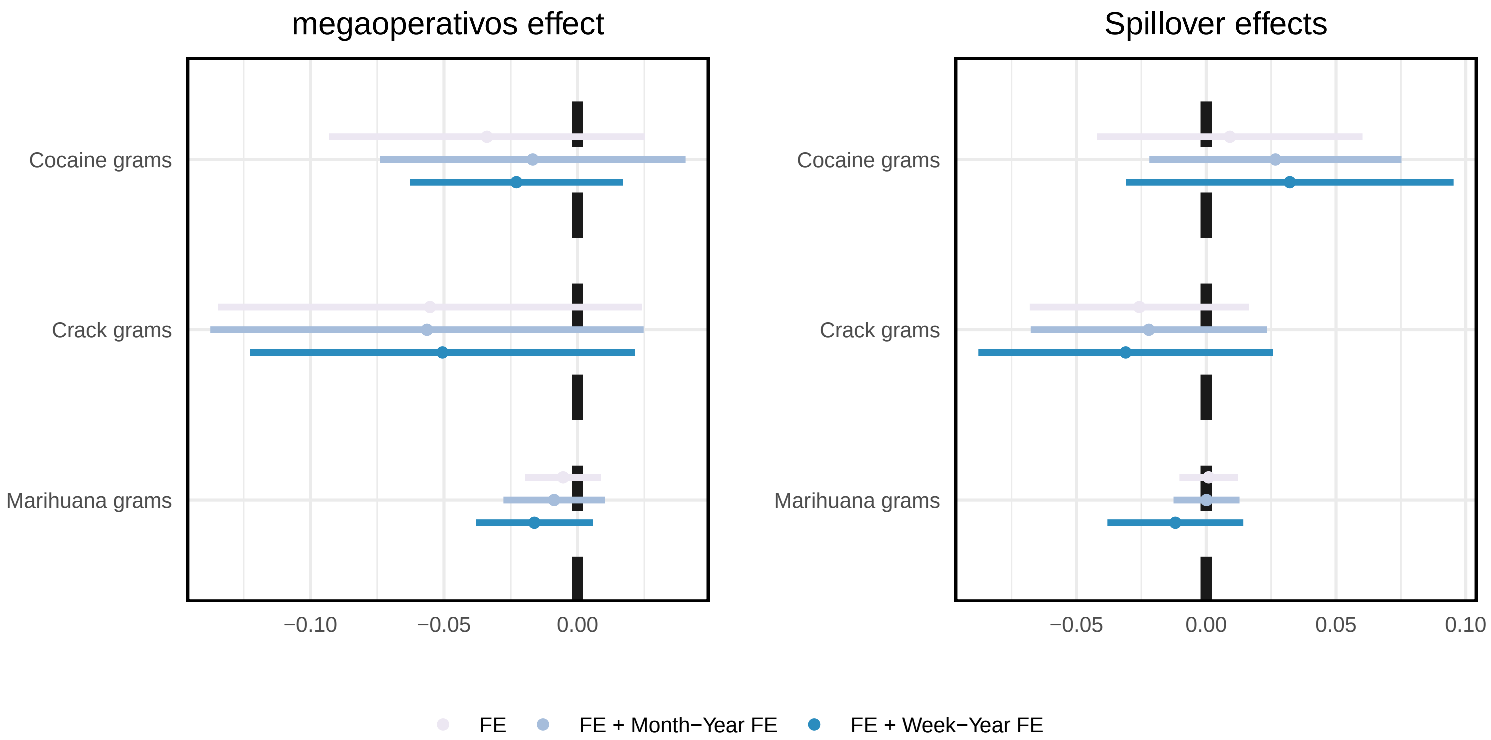
Notes: The left image shows the point estimates for the instantaneous effects of an additional megaoperativo along with their 95% confidence intervals. The right image shows the point estimates for the cumulative spillover effect of an additional megaoperativo on crime in districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Figure A24: cumulative effects on confiscated drug grams, extensive margin.



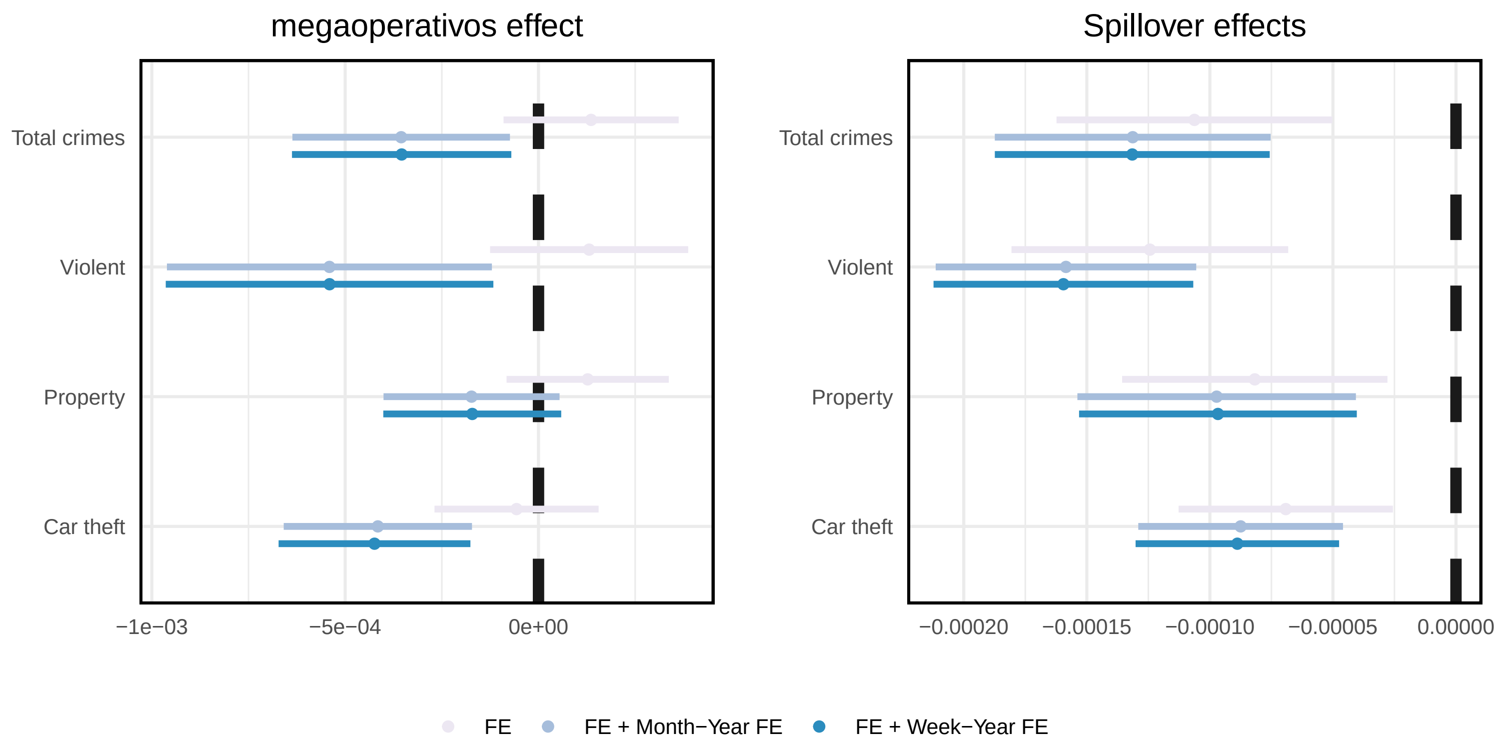
Notes: The left image shows the point estimates for the instantaneous effects of having megaoperativos along with their 95% confidence intervals. The right image shows the point estimates for the the instantaneous effects of having megaoperativos on crime on districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Figure A25: Instantaneous effects on confiscated drug grams, extensive margin.



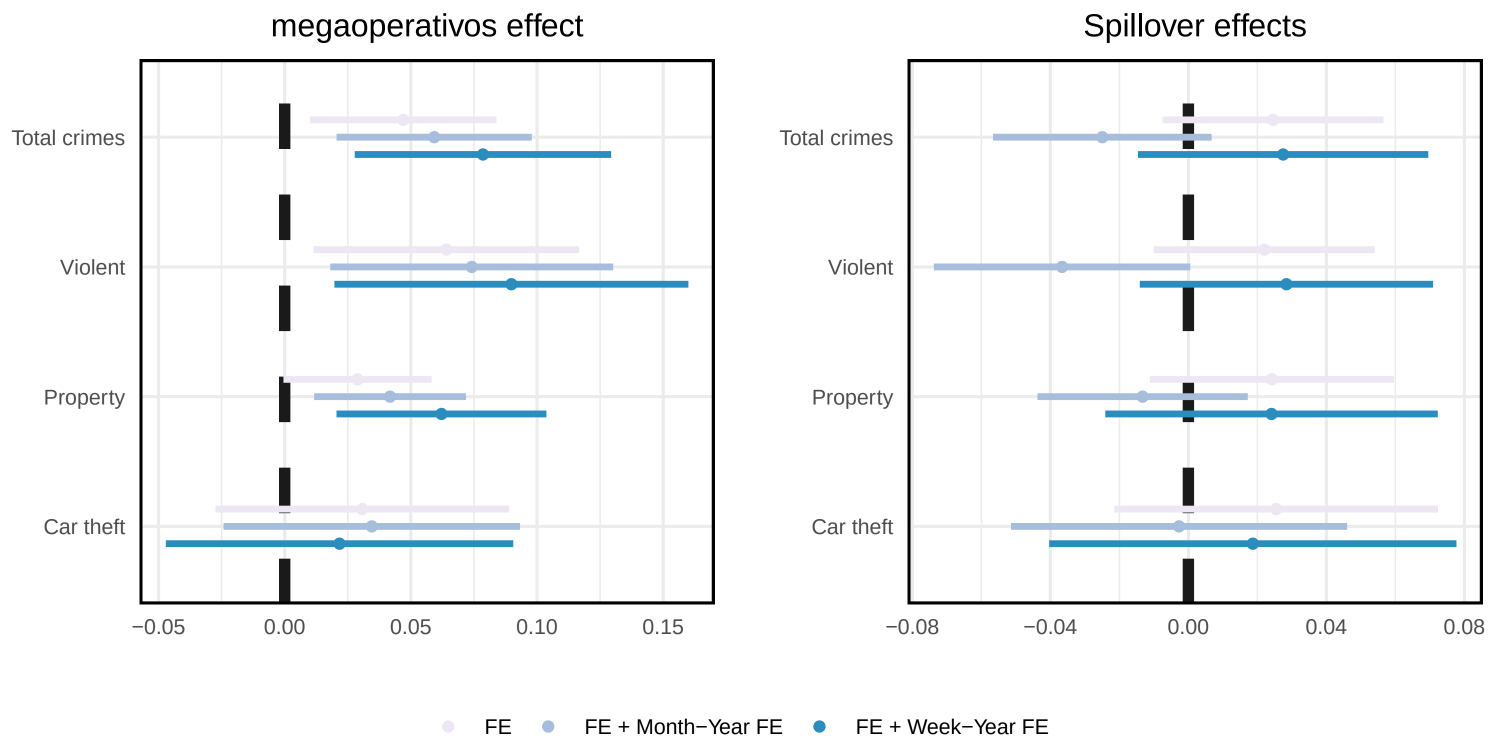
Notes: The left image shows the point estimates for the instantaneous effects of having megaoperativos along with their 95% confidence intervals. The right image shows the point estimates for the the instantaneous effects of having megaoperativos on crime on districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Figure A26: cumulative effects, intensive margin.



Notes: The left image shows the point estimates for the cumulative effects of an additional hour of megaoperativos along with their 95% confidence intervals. The right image shows the point estimates for the cumulative spillover effect of an additional hour of megaoperativos on crime on districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Figure A27: Instantaneous effects, intensive margin.



Notes: The left image shows the point estimates for the instantaneous effects of having megaoperativos along with their 95% confidence intervals. The right image shows the point estimates for the the instantaneous effects of having megaoperativos on crime on districts that did not have a megaoperativo along with their 95% confidence intervals. For both images, the dependent variable of interest is normalized, so each estimate indicates the effect on crime when the cumulative number of megaoperativos increases by one standard deviation. As the line gets darker, more controls are used in the econometric models. The model indicated by the lighter line uses district fixed effects, while the darker lines are models that control for district fixed effects and week-year fixed effects.

Figure A28: Detailed results, cumulative effects, intensive margin.

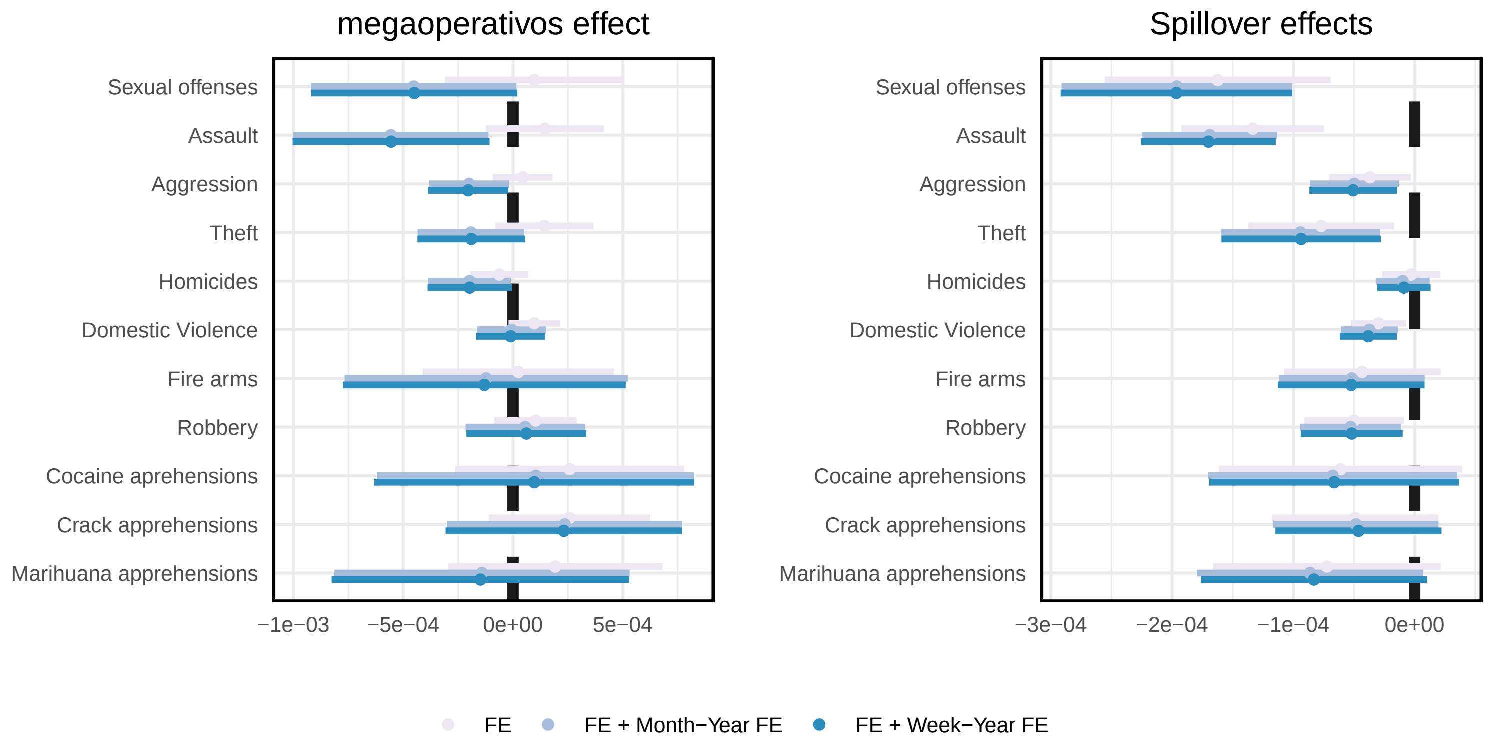


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Figure A29: Detailed results, instantaneous effects, intensive margin.

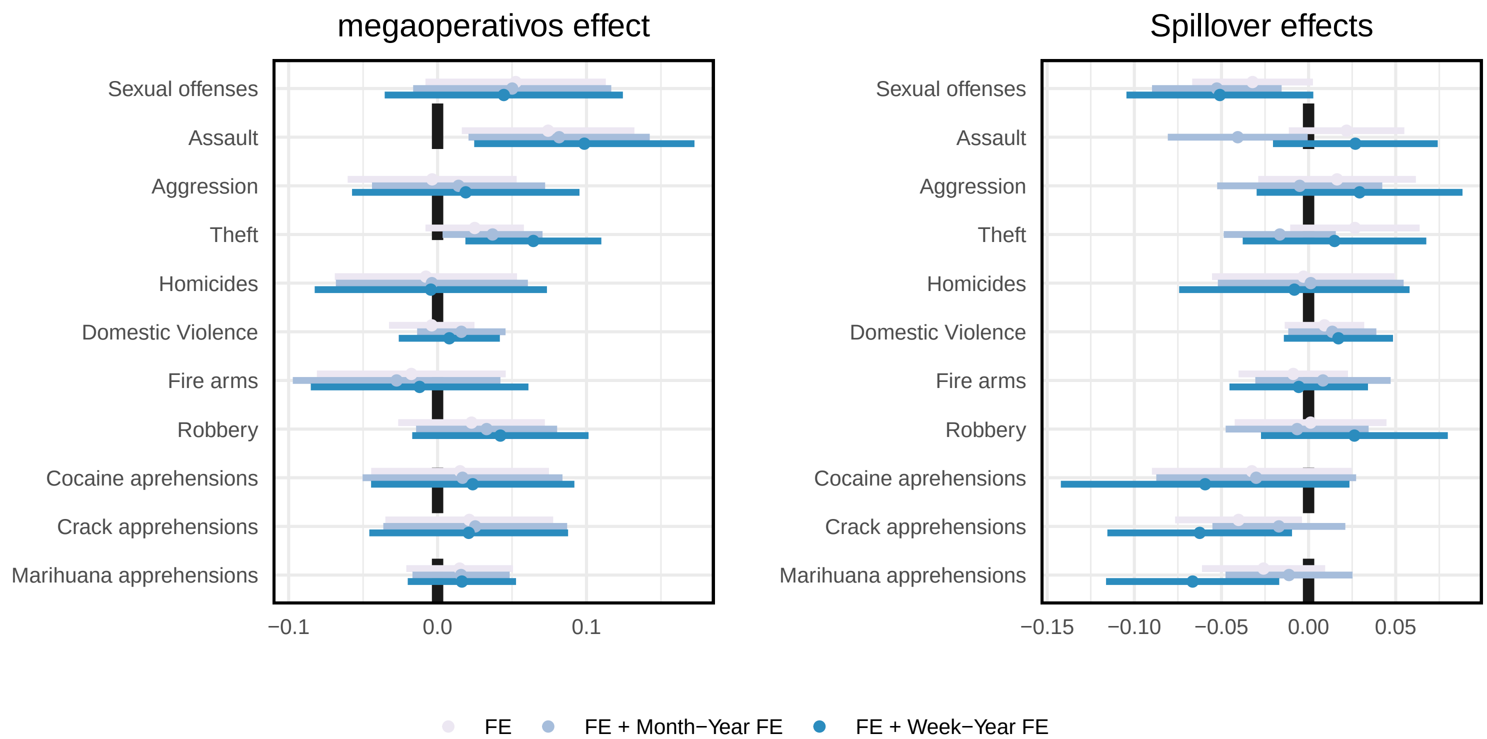

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Figure A30: cumulative effects on grams of confiscated drugs, intensive margin.

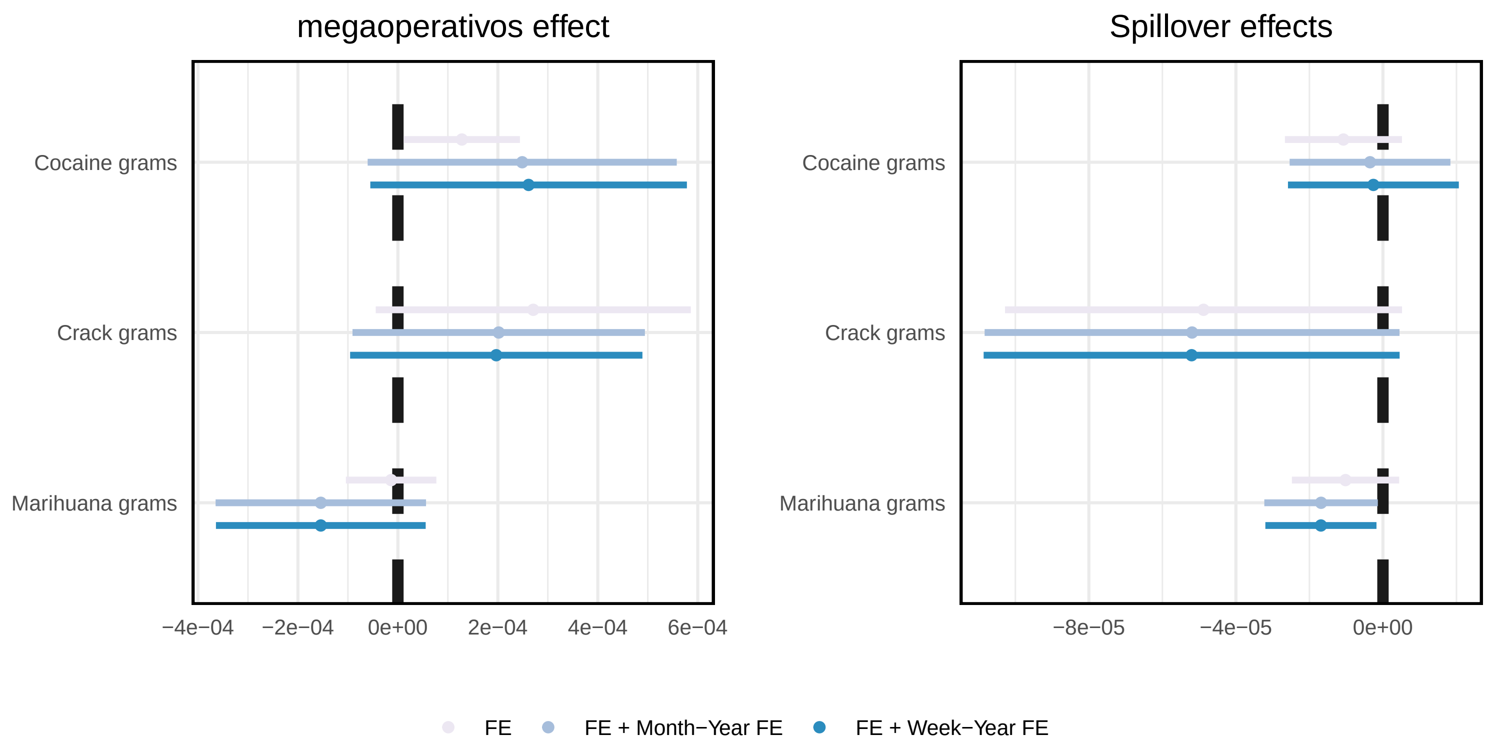

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Figure A31: Instantaneous effects on grams of confiscated drugs, intensive margin.

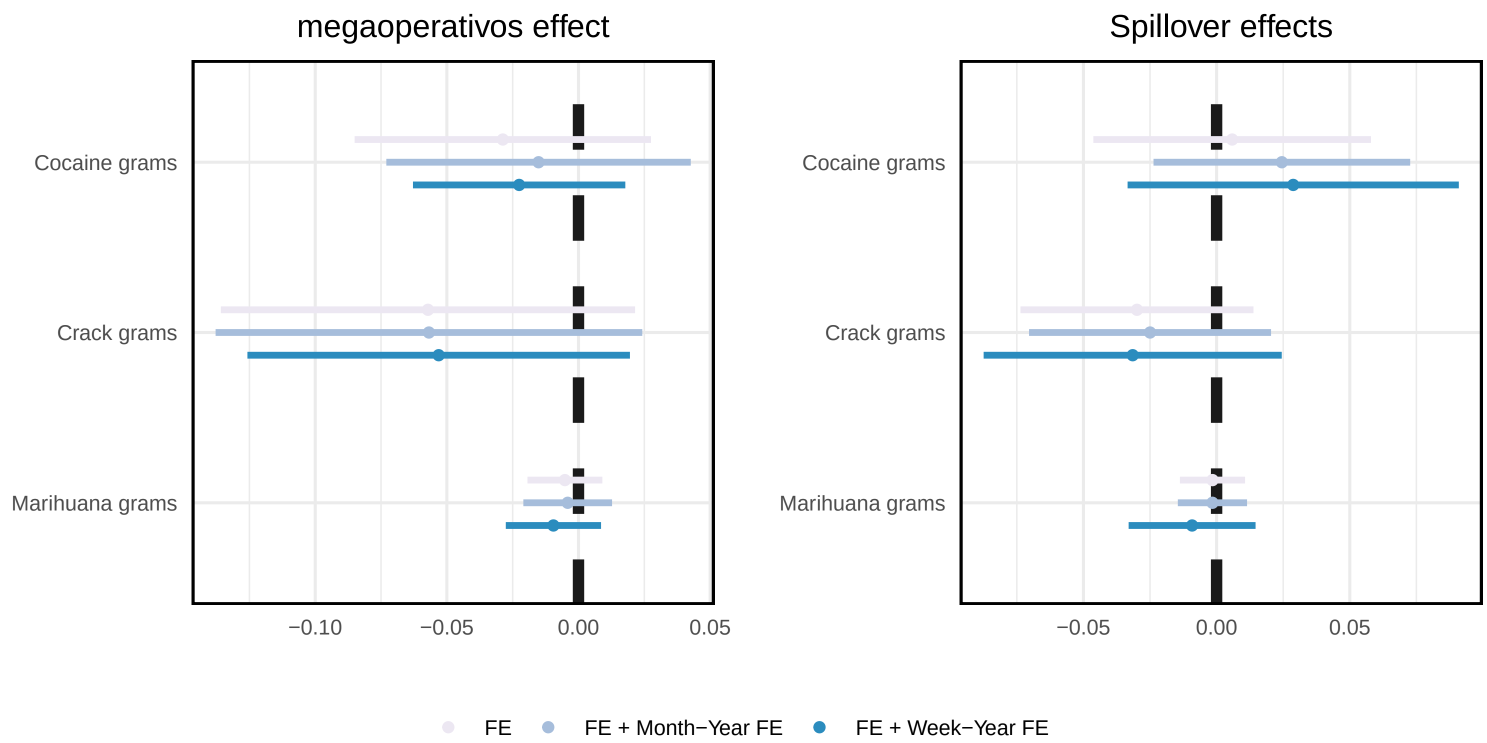

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Figure A32: Pre-pandemic cumulative effects, extensive margin

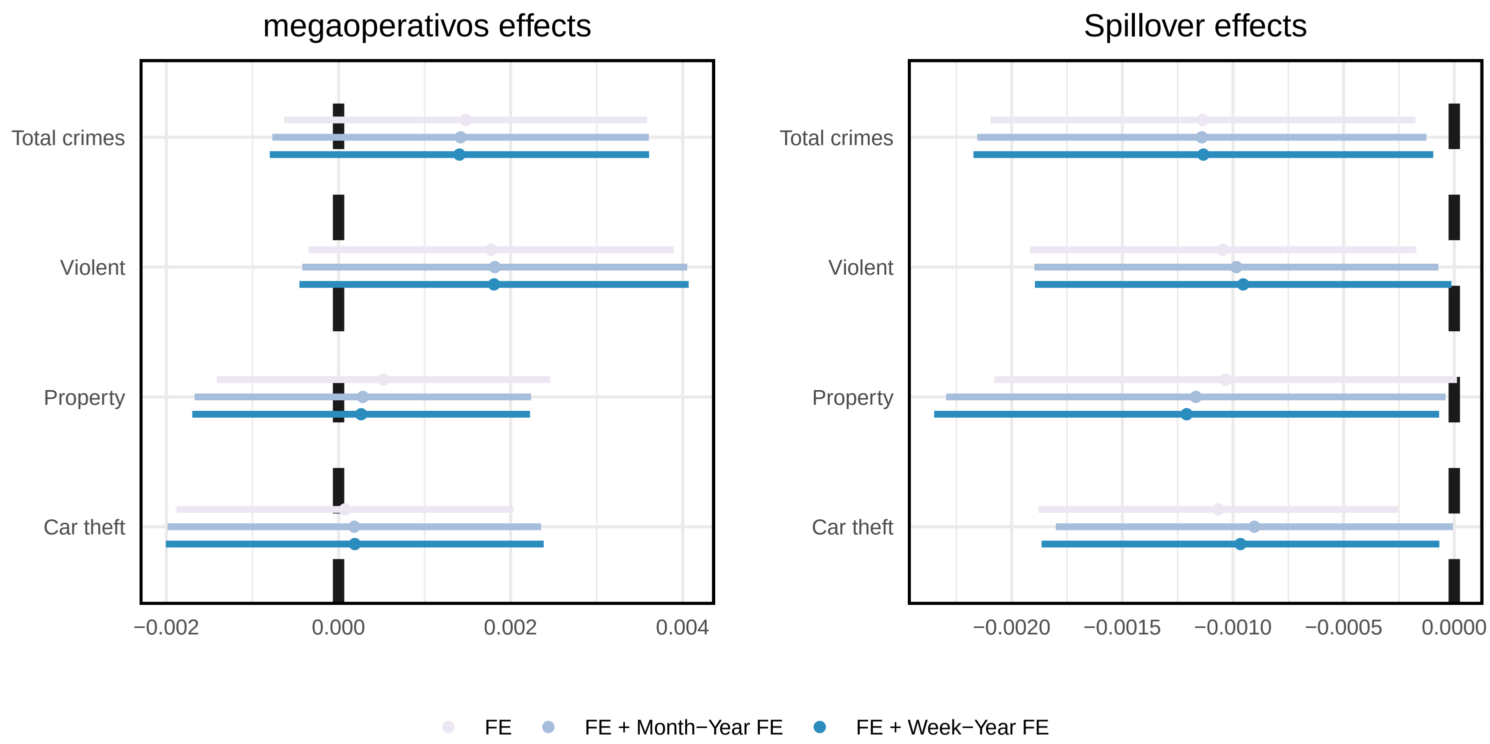

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Figure A33: Pre-pandemic instantaneous effects, extensive margin

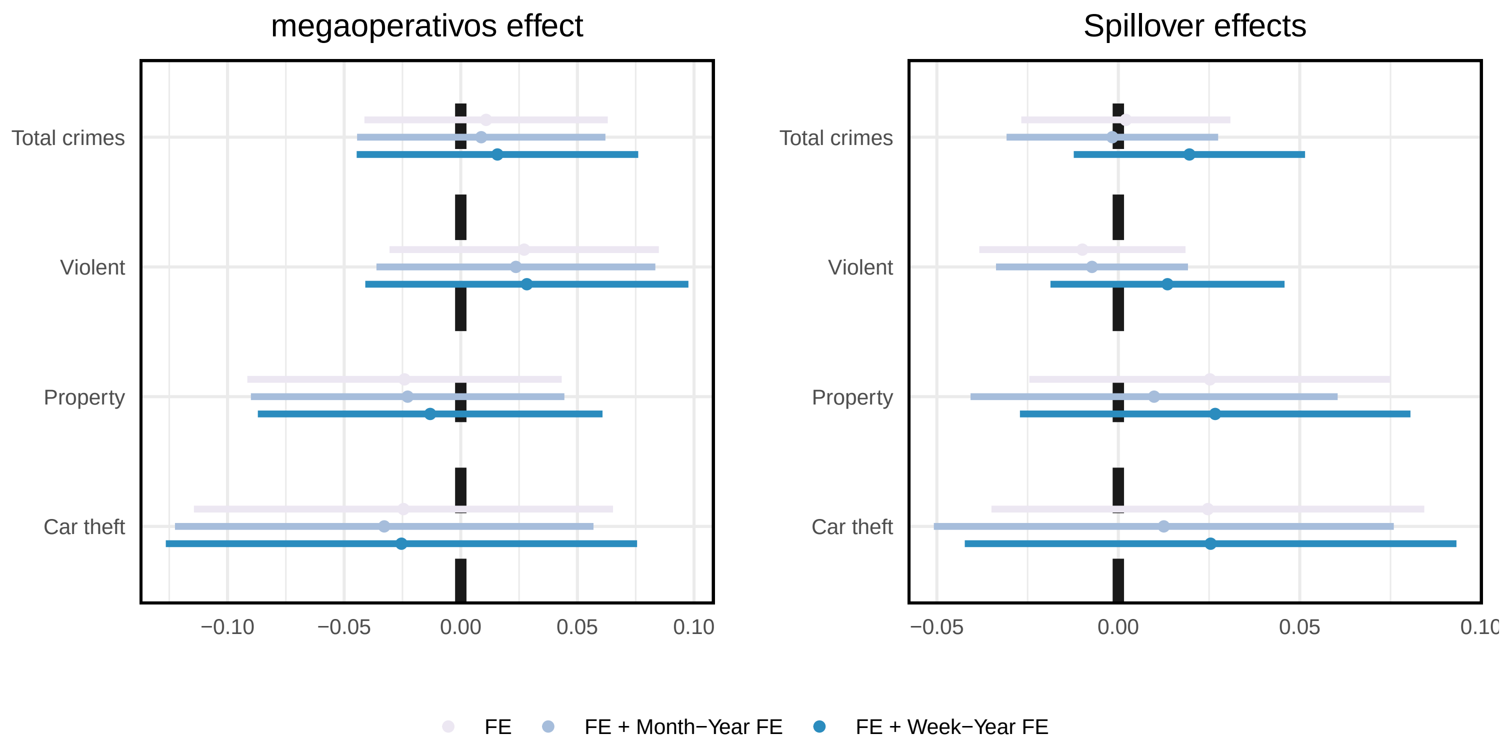

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Figure A34: Pre-pandemic cumulative effects, extensive margin

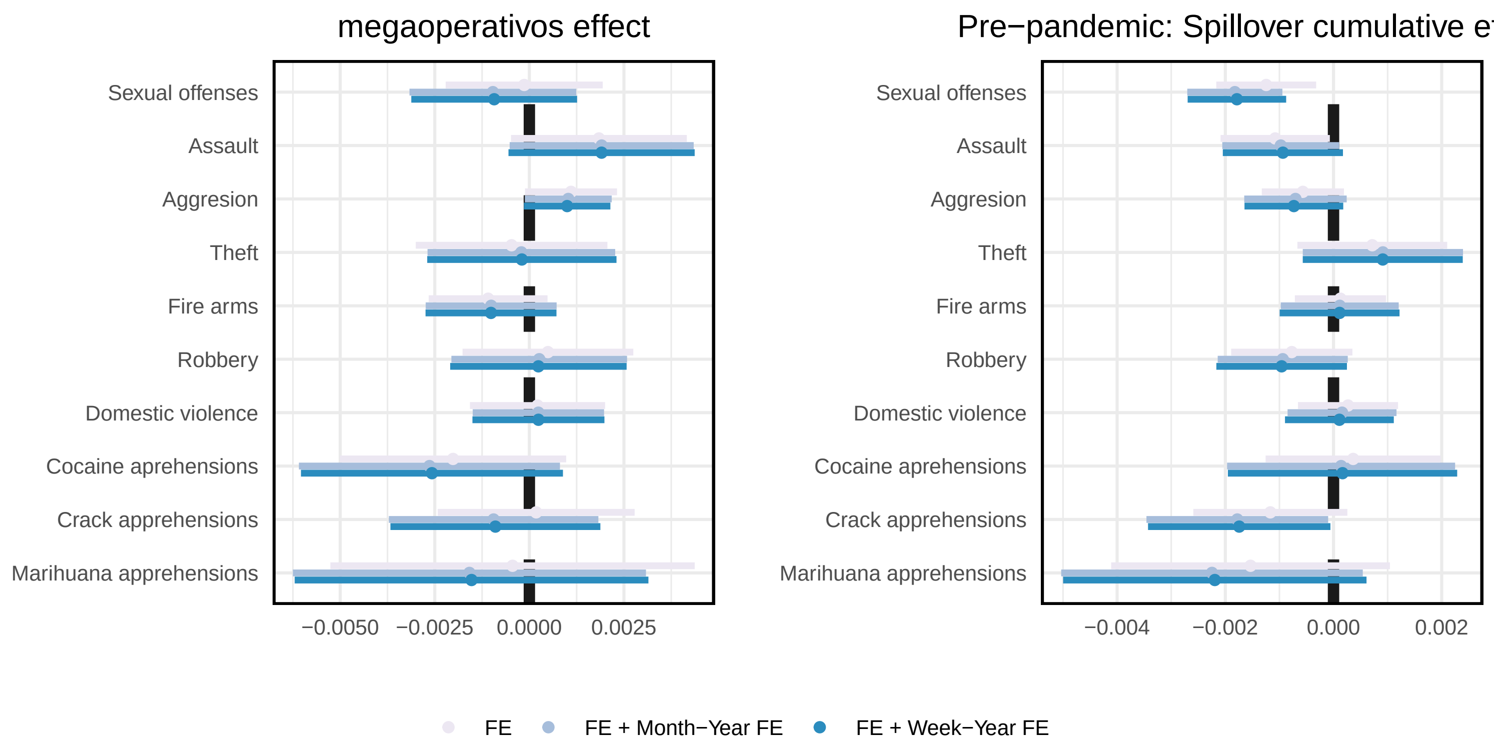

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Figure A35: Pre-pandemic instantaneous effects, extensive margin

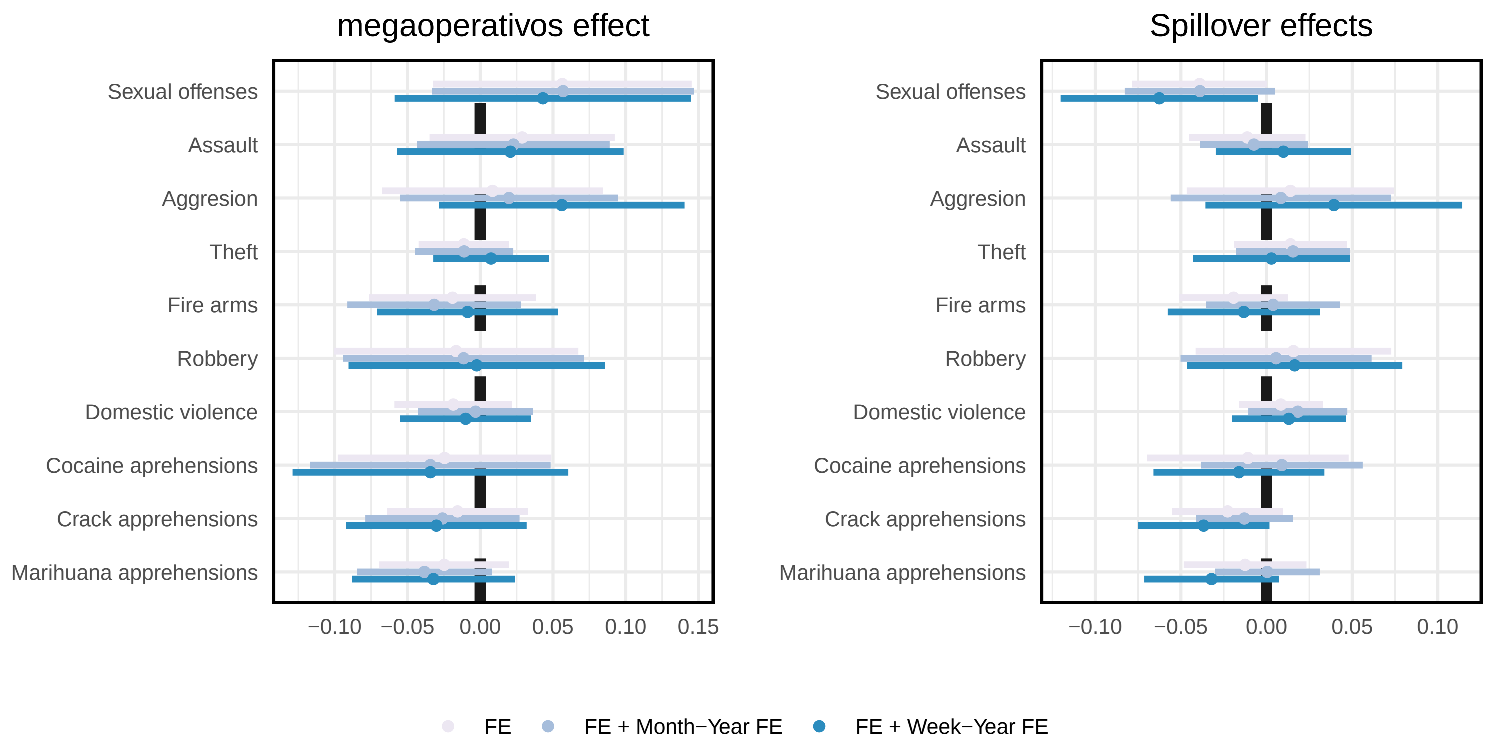

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Figure A36: Pre-pandemic cumulative effects on grams of confiscated drugs, extensive margin

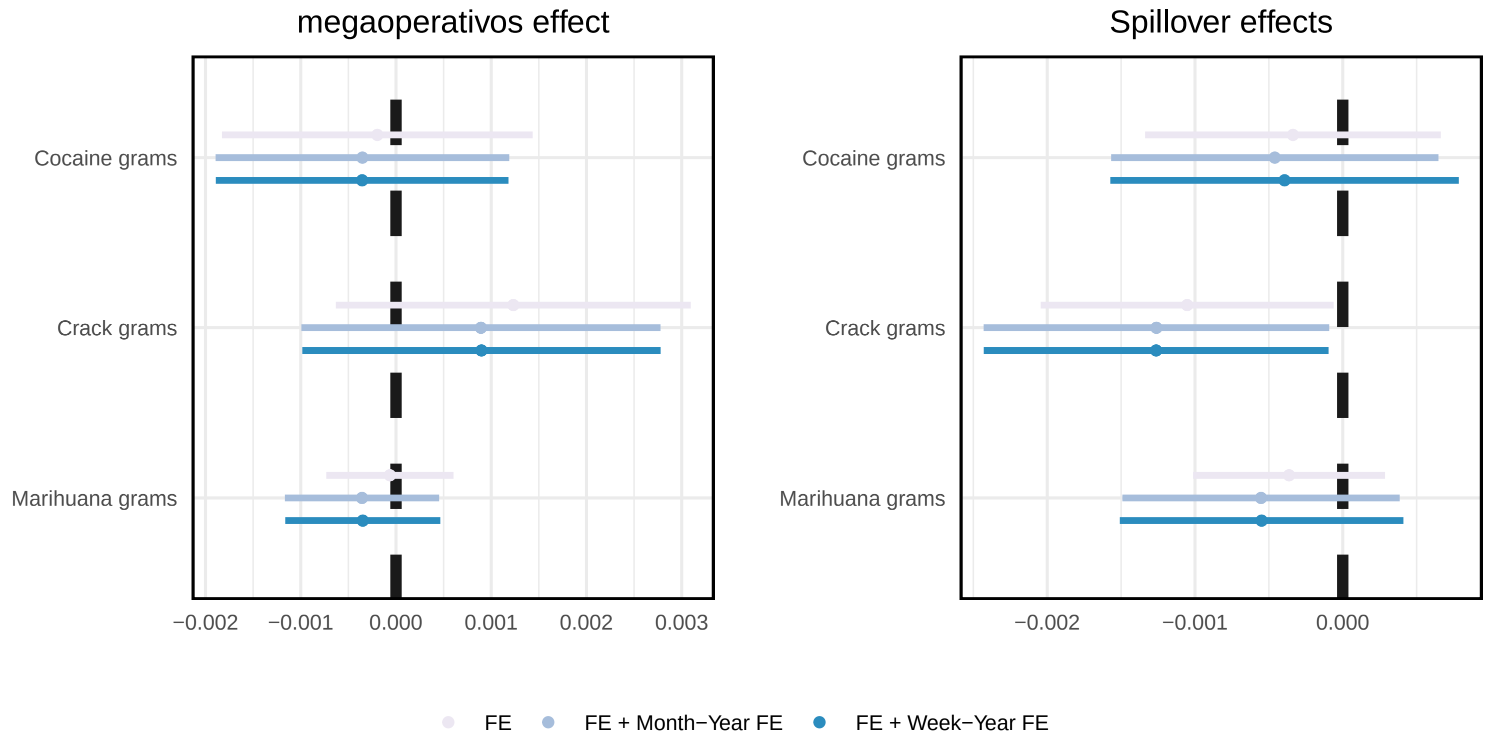

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Figure A37: Pre-pandemic instantaneous effects on grams of confiscated drugs, extensive margin

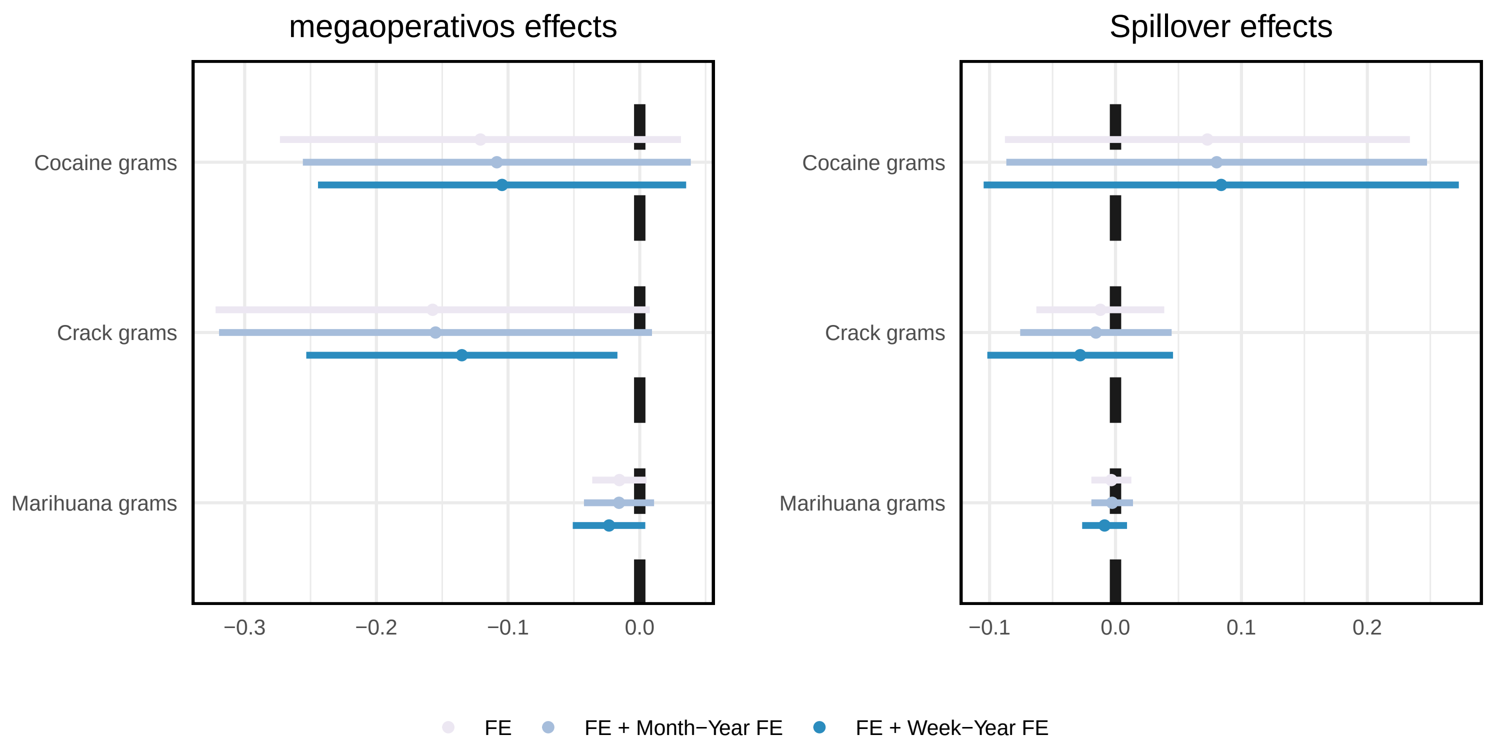

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Figure A38: Pre-pandemic cumulative effects, intensive margin

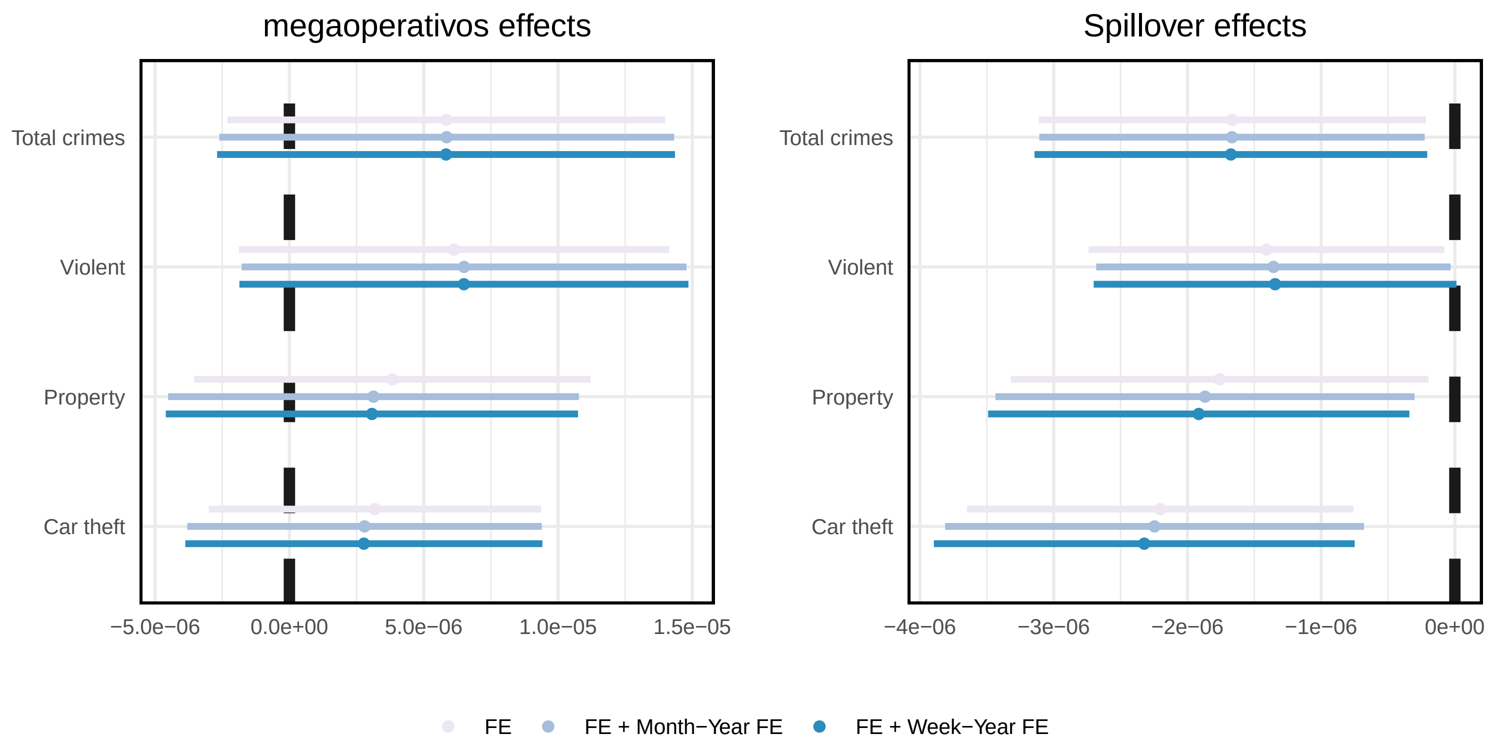

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Figure A39: Pre-pandemic instantaneous effects, intensive margin

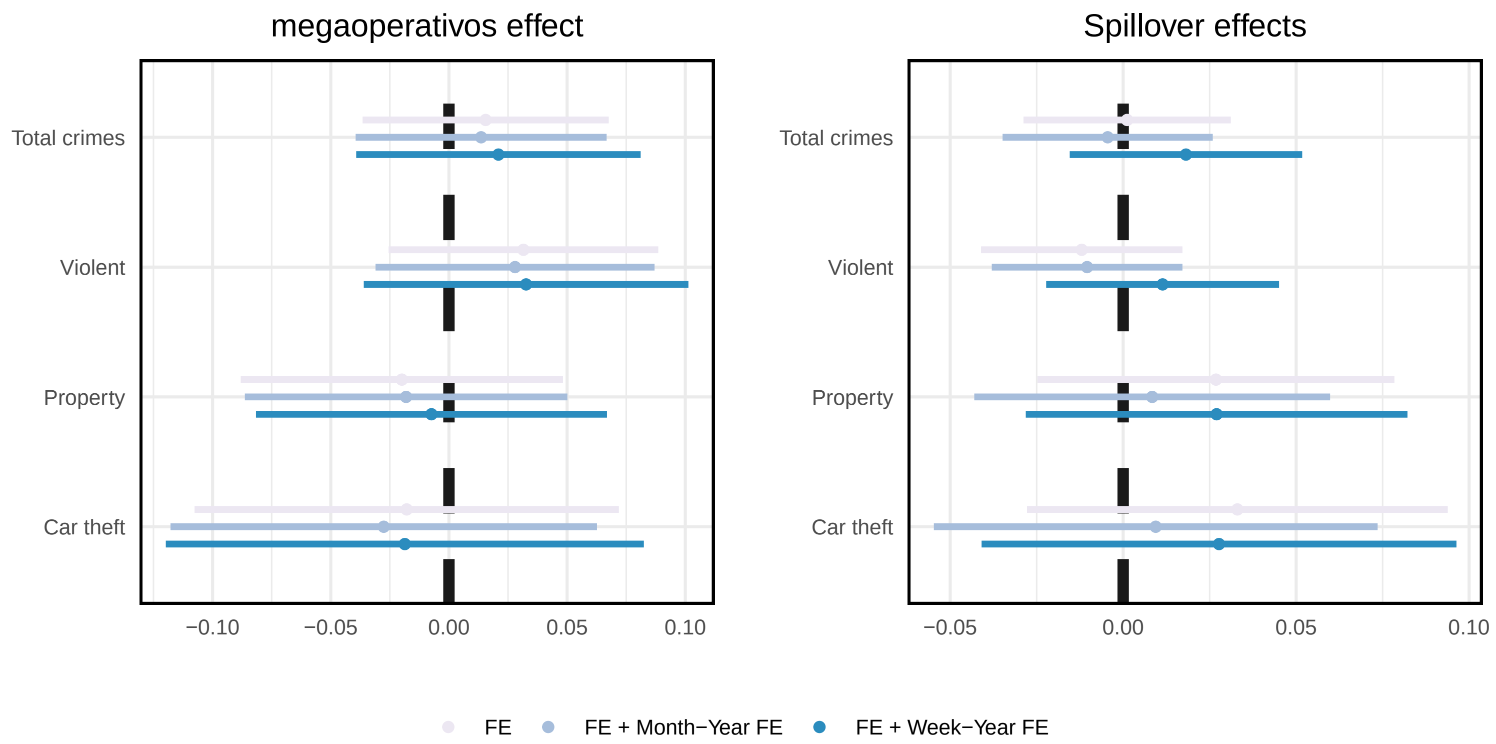

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Figure A40: Pre-pandemic instantaneous effects, detailed crimes, intensive margin

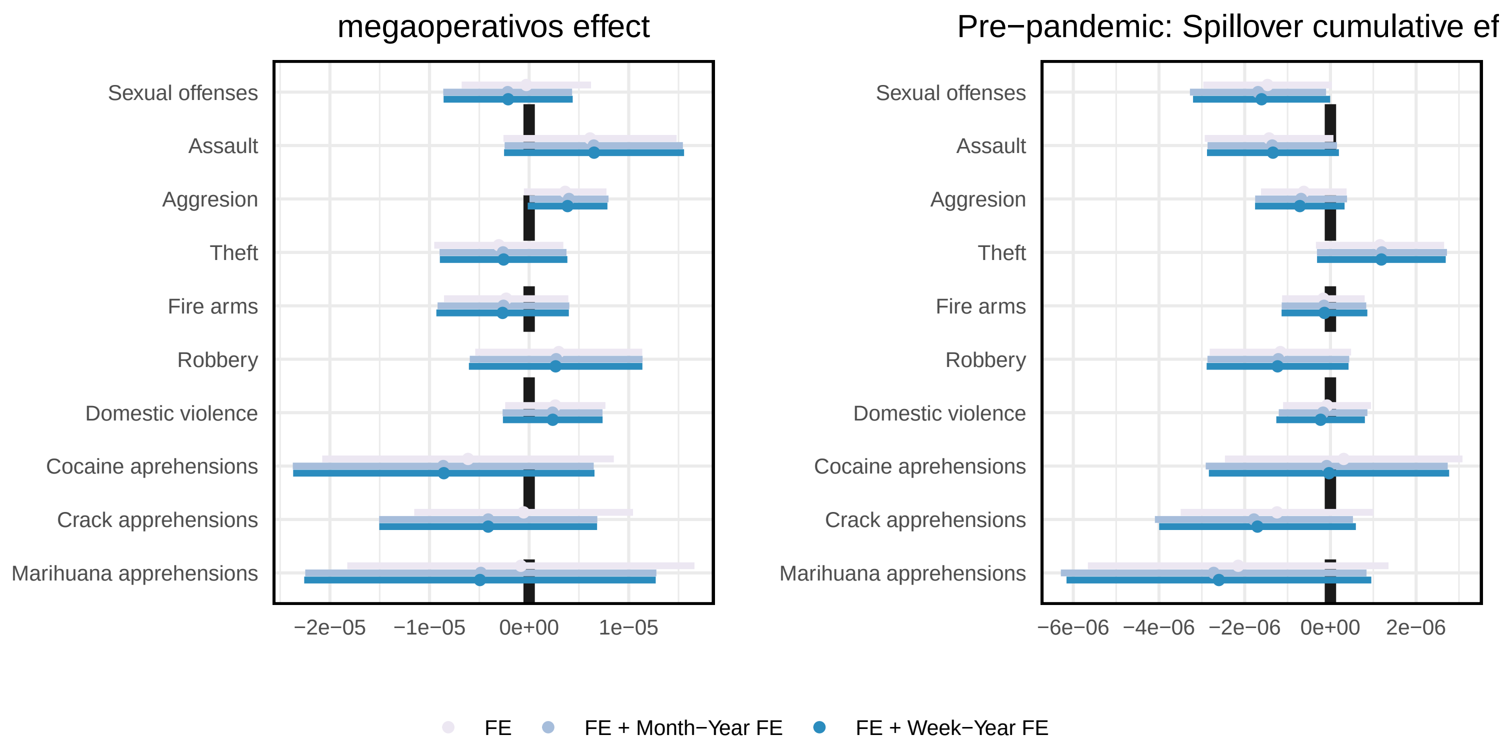

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Figure A41: Pre-pandemic instantaneous effects, detailed crimes, intensive margin

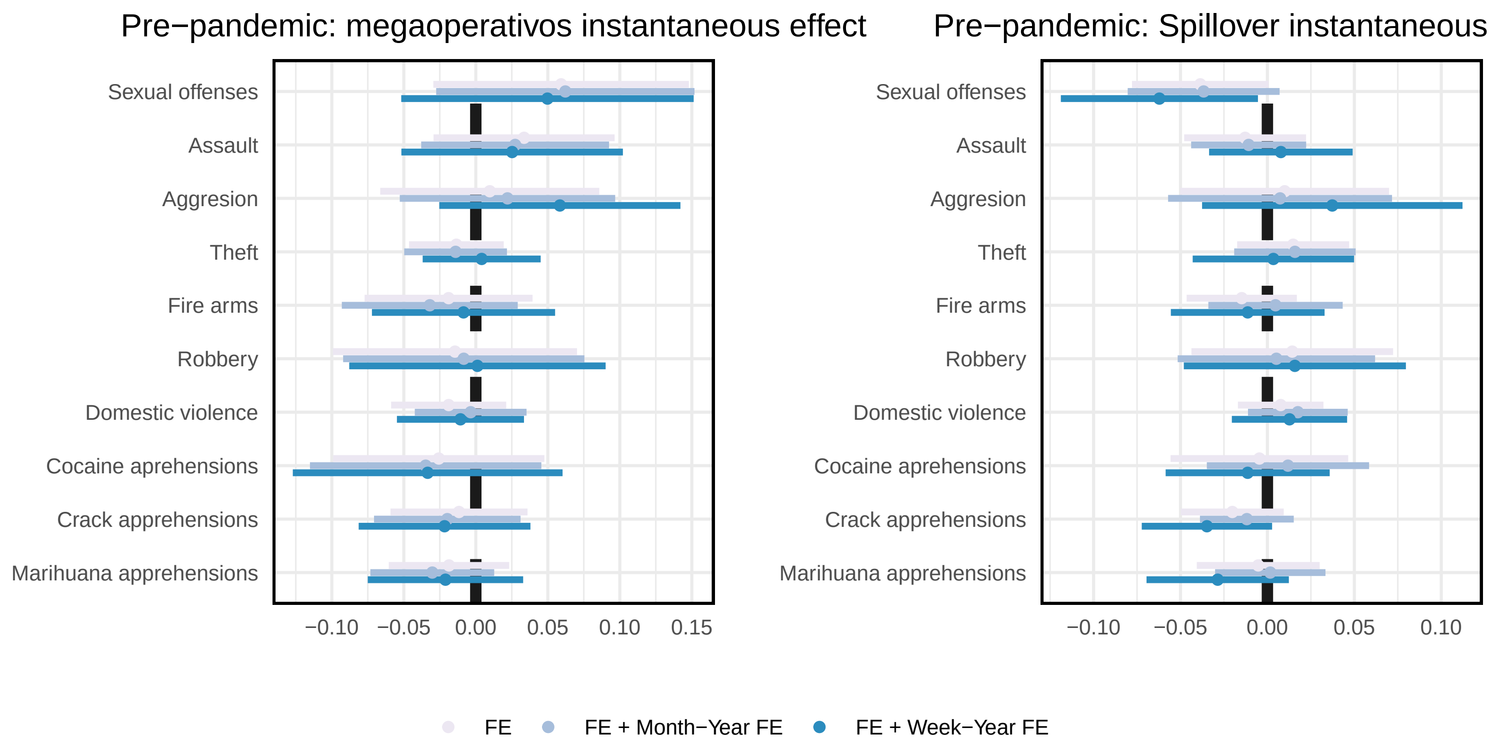

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Figure A42: Pre-pandemic cumulative effects on grams of confiscated drugs, intensive margin

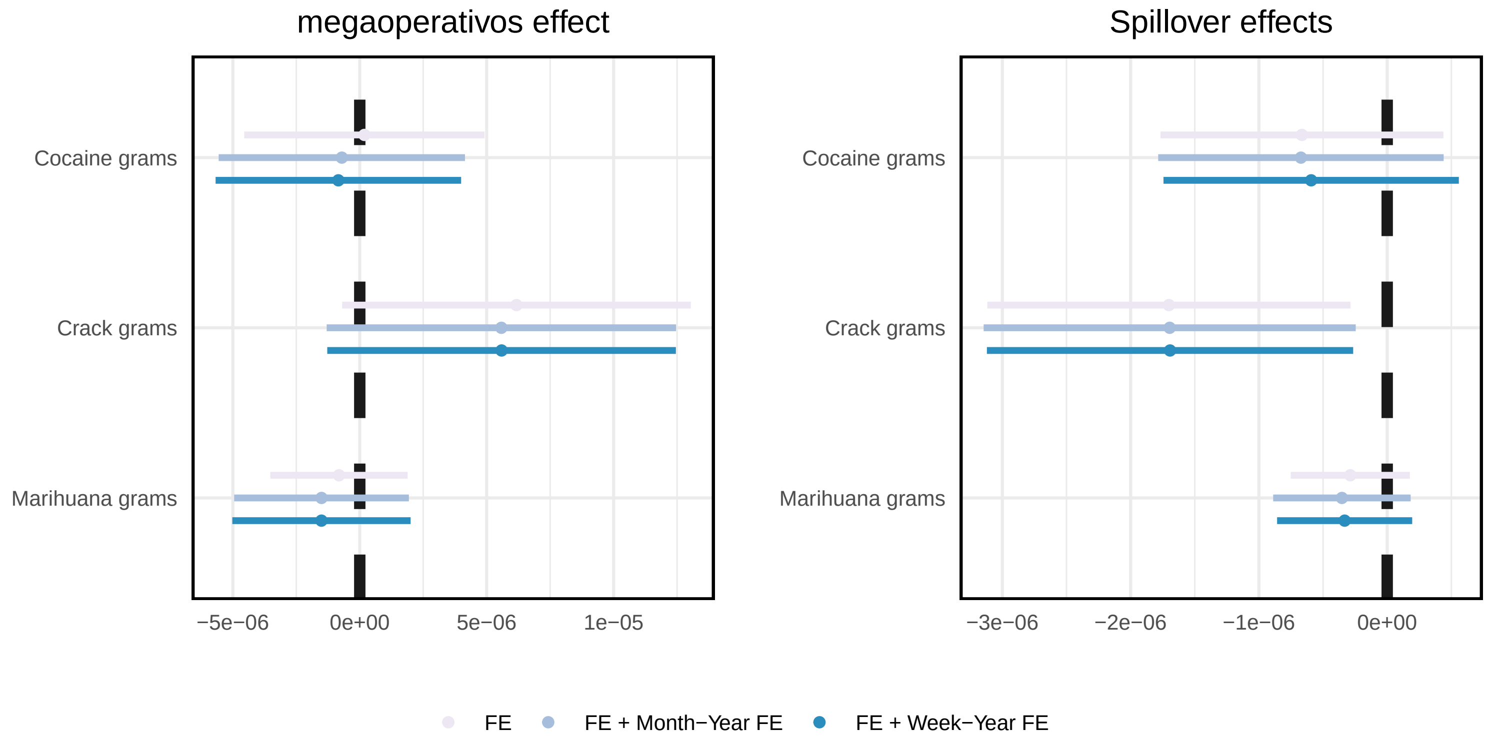

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Figure A43: Pre-pandemic instantaneous effects on grams of confiscated drugs, intensive margin

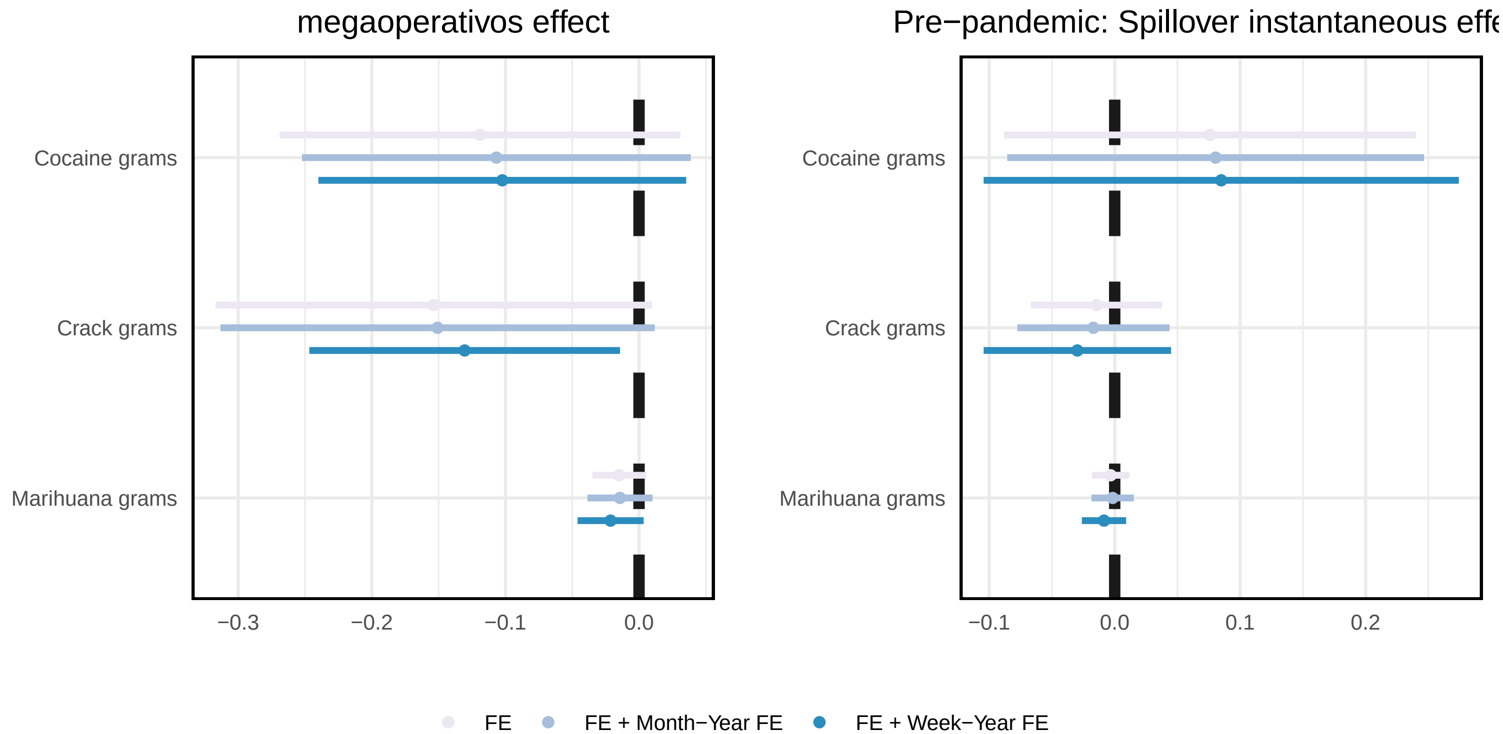

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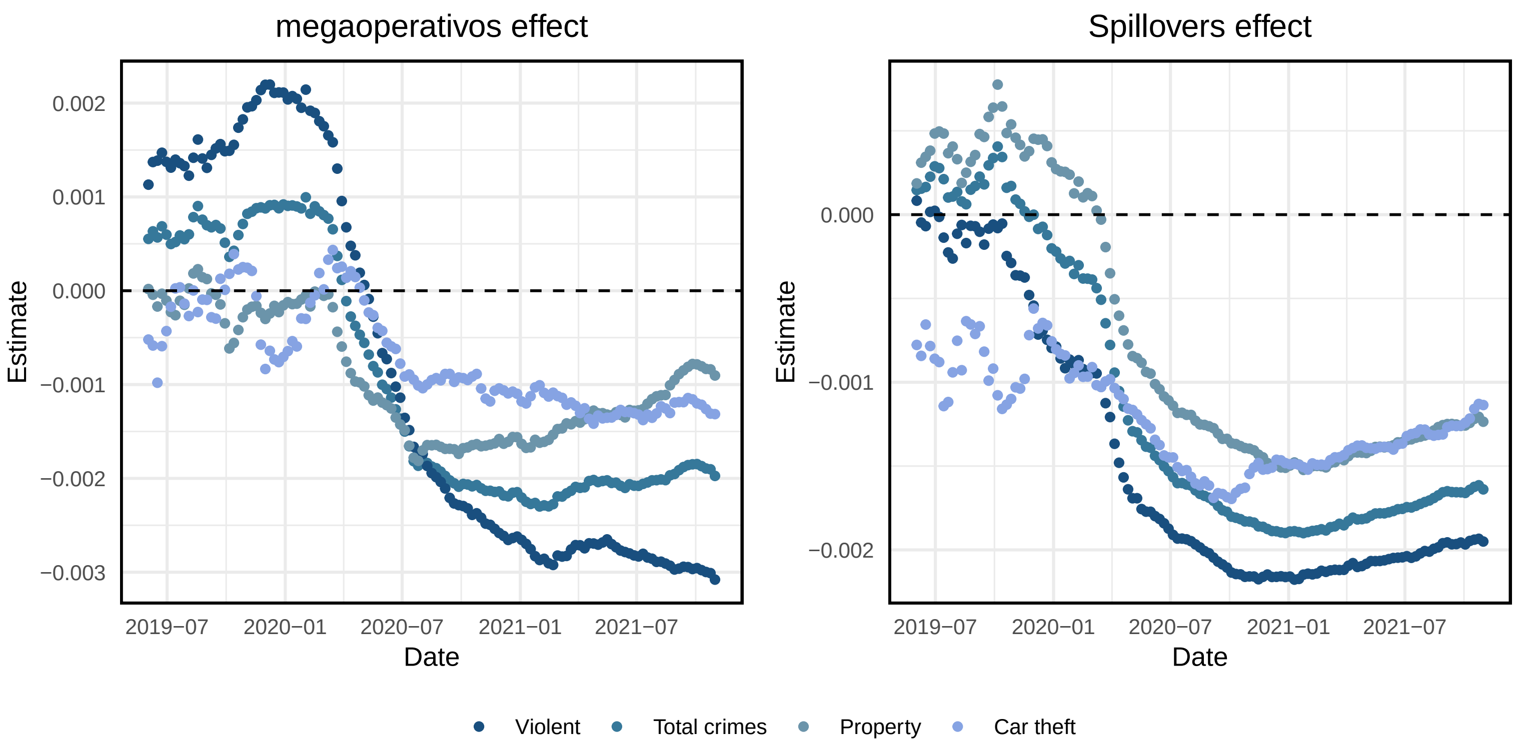
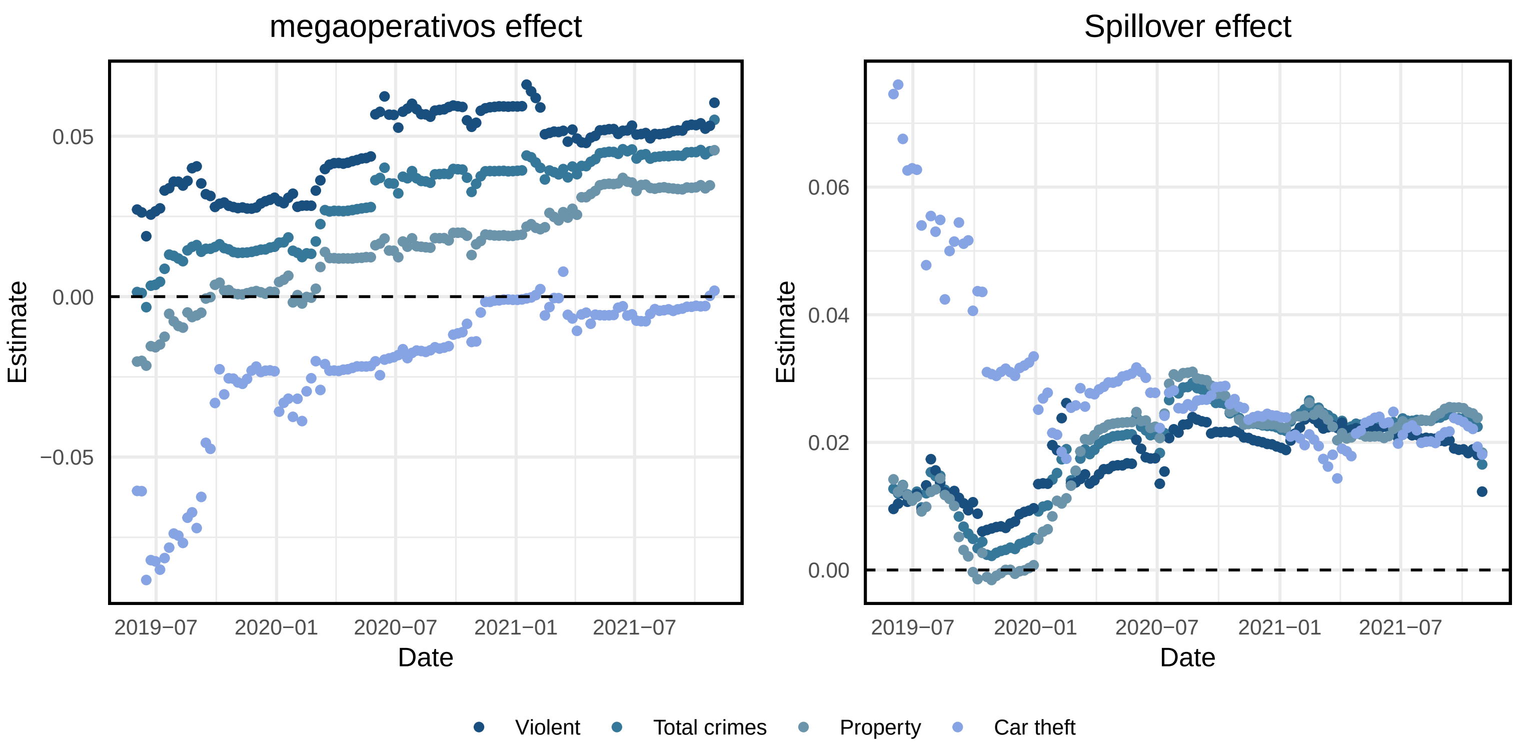
Figure A44: Week by week regressions, cummulative effects, extensive margin



Notes: The left image shows the point estimates for the MO cumulative effects for the extensive margin -number of MOs- when one week of data is added one by one. The image in the right shows the point estimates for the spillover cumulative effects for the extensive margin -number of MOs in surrounding districts- when one week of data is added one by one.

Figure A45: Week by week regressions, instantaneous effects, extensive margin



Notes: The left image shows the point estimates for the MO instantaneous effects for the extensive margin -number of MOs- when one week of data is added one by one. The image in the right shows the point estimates for the spillover instantaneous effects for the extensive margin -number of MOs in surrounding districts- when one week of data is added one by one.

Appendix 46: Leads test, detailed

	Dependent variable:						
	Sexual offenses	Assault	Aggression	Theft	firearms	Robbery	Domestic Violence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CumMO	-0.002^{**}	-0.009^{***}	-0.001^{***}	-0.004^{*}	-0.002	0.001	-0.006
	(0.001)	(0.003)	(0.0003)	(0.002)	(0.004)	(0.001)	(0.004)
CumSpillover	-0.001^{***}	-0.006^{***}	-0.0003^{***}	-0.003^{***}	-0.003^{***}	-0.001^{***}	-0.004^{***}
	(0.0002)	(0.001)	(0.0001)	(0.001)	(0.001)	(0.0004)	(0.001)
Lead MO	-0.052^{***}	0.093	0.012	0.063^{*}	-0.033	-0.001	0.230^{*}
	(0.019)	(0.065)	(0.016)	(0.032)	(0.050)	(0.028)	(0.124)
MO	0.017	0.175^{*}	0.004	0.126^{**}	-0.057	0.047	0.007
	(0.025)	(0.091)	(0.022)	(0.053)	(0.110)	(0.043)	(0.162)
Lead spillover	0.011	0.026	0.008	-0.050	-0.153^{**}	0.045	0.072
	(0.022)	(0.053)	(0.015)	(0.044)	(0.073)	(0.036)	(0.125)
Spillover	-0.040^{**}	0.017	0.009	0.027	0.007	0.026	0.093
	(0.018)	(0.064)	(0.017)	(0.073)	(0.075)	(0.037)	(0.149)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,691	25,046	25,046	25,046	20,691	25,046	20,691
Adjusted R^2	0.063	0.201	0.015	0.081	0.010	0.018	0.045

Note: *p<0.1; **p<0.05; ***p<0.01

Appendix 47: Leads test, drug crimes

	Dependent variable:					
	Cocaine aprehensions	Crack apprehensions	marijuana apprehensions	Cocaine grams	Crack grams	marijuana grams
	(1)	(2)	(3)	(4)	(5)	(6)
CumMO	0.00004	0.005	0.001	0.157	0.008	−0.197
	(0.002)	(0.003)	(0.016)	(0.095)	(0.053)	(0.122)
CumSpillover	−0.001	−0.002	−0.010	-0.028^{**}	−0.024	-0.124^{*}
	(0.001)	(0.001)	(0.006)	(0.013)	(0.028)	(0.066)
Lead MO	0.057	0.048	0.153	−2.038	−0.509	−2.163
	(0.050)	(0.048)	(0.160)	(1.927)	(2.105)	(4.312)
MO	0.024	0.031	0.033	−2.018	−5.187	−5.743
	(0.054)	(0.083)	(0.196)	(2.067)	(3.814)	(3.905)
Lead spillover	-0.128^{**}	-0.143^{**}	-0.713^{***}	1.081	−2.027	−3.533
	(0.056)	(0.061)	(0.260)	(1.634)	(2.455)	(4.710)
Spillover	−0.055	-0.093^{*}	-0.441^{*}	3.019	−2.651	−3.357
	(0.052)	(0.055)	(0.235)	(3.338)	(3.068)	(4.066)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-week FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,661	23,661	23,661	25,046	25,046	25,046

Note: *p<0.1; **p<0.05; ***p<0.01