Journal of Criminal Justice 72 (2021) 101745

Contents lists available at ScienceDirect

Journal of Criminal Justice

journal homepage: www.elsevier.com/locate/jcrimjus

Druglords don't stay at home: COVID-19 pandemic and crime patterns in Mexico City

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ARTICLE INFO

JEL:
J12
J16
J18

Keywords:
Crime
Organized crime
COVID-19
Mexico

ABSTRACT

Objective: To investigate the effect of the COVID-19 pandemic on conventional crime and organized crime in Mexico City, Mexico.
Methods: Mexico City's Attorney General's Office reported crime data, covering domestic violence, burglary, robbery, vehicle theft, assault-battery, homicides, kidnapping, and extortion. We use an event study for the intertemporal variation across the 16 districts (municipalities) in Mexico City for 2019 and 2020.
Results: We find a sharp decrease on crimes related to domestic violence, burglary, and vehicle theft; a decrease during some weeks on crimes related to assault-battery and extortion, and no effects on crimes related to robbery, kidnapping, and homicides.
Conclusions: While our results show a decline in conventional crime during the COVID- 19 pandemic, organized crime remains steady. These findings have policy implications for catastrophic events around the world, as well as possible national security issues in Mexico.

1. Introduction

After the COVID-19 pandemic began in 2020, governments around the world imposed a series of lockdowns. Non-essential businesses closed for several weeks, travel became difficult, social gatherings were limited, and officials from national and regional governments advised people to stay at home. All of these restrictions sought to accomplish social distancing, a vital public health tool used to contain the rapid growth of emerging infectious diseases (Fong et al., 2020). In essence, these stay-at-home orders modified most social structures, including criminal activity.

Until recently, research on the net effect of a large-scale lockdown on criminal activity was non-existent. New efforts within the criminal justice discipline are filling the knowledge gap. We aim to expand this literature by studying the effects of the COVID-19 pandemic on crime in Mexico City, using records from Mexico City's Attorney General's Office. The particular context of Mexico offers a glimpse into the effects of a lockdown on crime in a developing economy that shares many characteristics with other countries in Latin America. In particular, Mexico has a significant presence of organized criminal enterprises —besides conventional criminals—and institutional weaknesses in the criminal justice system.

The stay-at-home order time-line in Mexico City was similar to the rest of the world. In December 2020, an epidemic of a new coronavirus, SARS-CoV-2, emerged in Wuhan, China. The virus spread quickly throughout Asia (e.g. Iran) and then Europe (e.g., Italy and Spain) during the first three months of 2020, and made its way to North America in February 2020. On March 11, 2020, COVID-19 became a pandemic, as pronounced by the World Health Organization (WHO). The following week, restaurants, gyms, clubs, and universities began to shut down voluntarily in Mexico City. On March 23, 2020, the federal government officially started the "social distancing" campaign, and the whole country went under lockdown. Schools, government offices, malls, parks, and non-essential businesses closed temporarily down in Mexico City.

Following the lockdown, mobility in Mexico City decreased by around 70% (Apple, 2020), even though the stay-at-home order was not a strictly-enforced policy. Fig. 1 shows mobility trends for driving, walking, and transit in Mexico City, using data from Apple Mobility Trends Reports. All traffic variables significantly drop one week prior to the official lockdown. The mobility data suggests that the COVID-19 pandemic provides a natural experiment to examine whether a large-

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https://doi.org/10.1016/j.jcrimjus.2020.101745
Received 4 August 2020; Received in revised form 15 September 2020; Accepted 15 September 2020
Available online 24 September 2020

scale lockdown affects crime.

We use data covering conventional crime such as domestic violence, burglary, robbery, vehicle theft, and assault-battery to test the effect of the pandemic COVID-19 on crime. Then, we study whether organized crime behaves differently than conventional crime by exploiting the variation of certain variables linked to drug-trafficking organizations in Mexico. These activities include homicides, kidnapping, and extortion. For our analysis, we use weekly data of these crimes per 100,000 inhabitants, for the 16 districts (municipalities) in Mexico City. We use the intertemporal variation from these crime rates over January to May for 2019 and 2020. Using an event-study design, we find: (1) a sharp decrease on crimes related to domestic violence, burglary, and vehicle theft; (2) a decrease during some weeks on crimes related to assault-battery and extortion, and (3) no effect on crimes related to robbery, kidnapping, and homicides.

The findings from this study make several contributions to the literature surrounding crime and COVID-19. First, there is no conclusive evidence regarding the effects of COVID-19 on domestic violence and vehicle theft. We find a decrease in domestic violence, which confirms findings from India (Poblete-Cazenave, 2020) and the United Kingdom (Halford et al., 2020). Despite these findings, in the United States, Mohler et al. (2020) found an increase in domestic violence for Indianapolis and Los Angeles. We also observe a decrease in vehicle theft, which confirms results from Canada (Hodgkinson and Andresen, 2020) and the UK (Halford et al., 2020). However, Mohler et al. (2020) found no effect regarding vehicle theft for Indianapolis and an increase in Los Angeles. Second, we corroborate findings from India (Poblete-Cazenave, 2020), the USA (Mohler et al., 2020), Canada (Hodgkinson and Andresen, 2020), and the UK (Halford et al., 2020), where a reduction on burglary is observed. We also confirm findings from India (Poblete-Cazenave, 2020) and the USA (Mohler et al., 2020), for a reduction in robberies. Third, we find evidence that homicides and kidnapping remained the same, which contrasts with the decrease seen in India (Poblete-Cazenave, 2020) and Peru (Calderon-Anyosa and Kaufman, 2020). To our knowledge, this is the first paper to explore the effects of a pandemic on crime in Mexico.

Our paper relates theoretically to a body of literature that studies the effects of catastrophic events on crime (Fritz, 1996; Zahran et al., 2009; Curtis et al., 2000; Davila et al., 2005; Di Tella and Schargrodsky, 2004; Nel and Righarts, 2008). One thread of this literature examines criminals' behavioral changes due to disruptions in the activities of potential victims (Fritz, 1996; Zahran et al., 2009; Curtis et al., 2000; Davila et al., 2005). Another piece of this literature studies how exceptional events modify police's presence and whether this, in turn, affects crime (Di Tella and Schargrodsky, 2004; Nel and Righarts, 2008).

First, the literature that studies the effects of catastrophic events on criminal behavior relies upon theoretical explanations from the criminal justice and sociology fields. We identify two theoretical explanations. First, prosocial theories predict a drop in crime after a catastrophic event due to the altruistic behavior of criminals (Fritz, 1996; Zahran et al., 2009). Second, antisocial theories forecast a rise in crime following a catastrophic event due to criminals' opportunistic behavior or a change in routine activities (Curtis et al., 2000; Davila et al., 2005). In comparison, the former theory proposes an underlying "therapeutic community" that promotes the rebuilding of social cohesion across social classes (Fritz, 1996), while the latter approach suggests that disasters present a "rich environment" for criminals, where "social disorganization," chaos, and a fall in social capital prevails (Davila et al., 2005).

The second part of the literature studies the impact on crime of exceptional events that shift the supply of order forces (e.g., police, military, paramilitary, or vigilante). For instance, terrorist attacks customarily increase the number of police who move to a city or a particular district that was subject to the attack, causing a decline in crime because of police presence (Di Tella and Schargrodsky, 2004; Draca et al., 2011). Additionally, military patrols might take over the control of certain parts of the city after a natural disaster, affecting general violence (Nel and Righarts, 2008).

The remainder of this paper proceeds as follows. In Section 2, we review the new literature analyzing the relationship between COVID-19 and crime. Section 3 describes the crime data for Mexico City and empirical methods. Section 4 presents the main findings and a series of robustness tests. Section 5 discusses the implication of our results for the future of organized criminal enterprises in Mexico, and Section 6 concludes.

2. COVID-19 and crime

Restrictions on mobility from attempted containment of COVID-19 may reduce virus transmission and these restrictions may affect other social interactions, including crime. The developing literature on the effects of the COVID-19 pandemic explores the cases of different cities in North America, including Indianapolis, Los Angeles, and Vancouver, as well as in Asia with Bihar's case. Emerging papers also study the effect of the pandemic on crime for countries such as Peru and the UK.

Mohler et al. (2020) uses data on service calls in Indianapolis, USA, and Los Angeles, USA, to make comparisons before and after the lockdown. Mohler et al. (2020) found an increase in domestic violence, a decrease in robbery and burglary, but find no effect on assault-battery. The authors also observe mixed results for vehicle theft; in particular, they find no impact on Indianapolis, and an increase in Los Angeles.

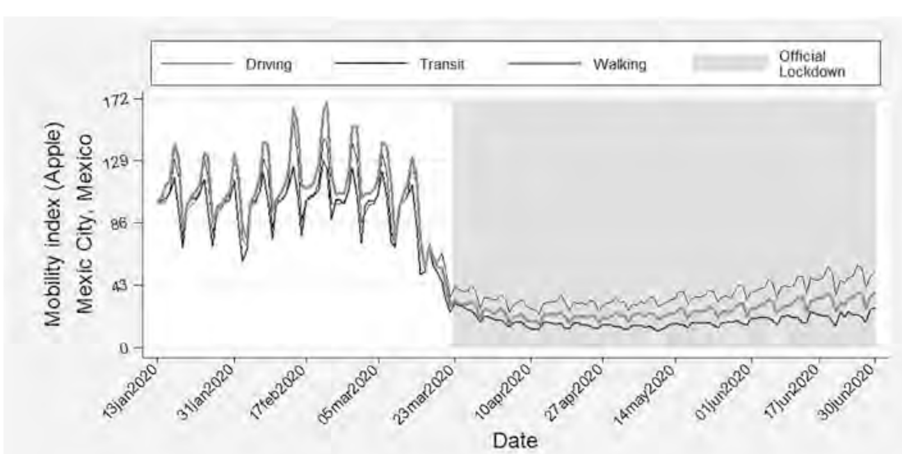

Fig. 1. Mobility in Mexico city.
SOURCE: Apple Mobility Trends Reports (2020)

Hodgkinson and Andresen (2020), using crime data from Vancouver, Canada, and interrupted time series techniques, found evidence of a decrease in residential burglary, commercial burglary, and vehicle theft. Poblete-Cazenave (2020), using first information report data from Bihar, India, and a regression discontinuity design, found that the COVID-19 lockdown decreased aggregate crime by 44%. The shutdown lowered domestic violence, burglary, robbery, kidnapping, and murder.

Calderon-Anyosa and Kaufman (2020) uses an interrupted time series and found evidence of a decrease in homicides in Peru. Halford et al. (2020), employing data from the UK, found a reduction in aggregate crime by 41%. The crime decline impacted domestic abuse, burglary, assault-battery, and vehicle theft.

The literature supports the hypothesis that the COVID-19 pandemic may decrease robbery, burglary, and assault-battery. The body of work also suggests a decrease in homicides and kidnapping. Despite these consistent declines, there is no conclusive evidence for domestic violence and vehicle theft.

3. Empirical strategy

3.1. Data

To estimate the effects of the COVID-19 lockdown on crime, we use administrative data from Mexico City's Attorney General's Office (Attorney General's Office, M. C, 2020). This source covers the reports for the following offenses: 1) domestic violence, 2) burglary, 3) robbery, 4) vehicle theft, 5) assault-battery, 6) homicides, 7) kidnapping, and 8) extortion. We use the first five types of crime as indicators for conventional crime, and the latter three are proxies for organized crime. The main reason to think of homicides, kidnapping, and extortion as measures of organized crime resides on the so-called Mexican drug war.

The expansion of organized criminal enterprises and violence is relatively recent. On December 11, 2006 newly elected President Felipe Calderón declared a war on drug-trafficking organizations. In the subsequent years, the violence spread around the country. The number of municipalities with a rate of 12 homicides per 100,000 inhabitants or more increased from 48 municipalities to 148 municipalities between 2007 and 2010 (Brown et al., 2015). One of the main strategies for fighting organized crime was the capture of its leaders. Lindo and Padilla-Romo (2018) find that the capture of a kingpin in a municipality increases its homicides rate by 61% in the six months following the capture and this effect persist into subsequent periods. This suggests that most of the homicides observed in Mexico in the last years are related to organized crime. In addition, recent evidence suggest that as narco-business expands some organizations diversify their criminal portfolio by engaging in kidnapping, extortion, and other profitable business (Bergman, 2018). Namely, the literature identifies that the kingpin capturing strategy led to an increase in kidnapping rates (Jones, 2013). Similarly, turf wars between Mexican cartels produced more extortion as a way to coerce society (Magaloni et al., 2020). Therefore, in Mexico, homicides, kidnapping and extortion are criminal activities mostly carried out by organized criminal enterprises.

Moreover, Mexico's new model of criminal justice set nobel guidelines for all Mexican States, including Mexico City, to transition from an inquisitorial to an adversarial criminal law system. In 2018, Mexico City implemented its new model to receive reports for crimes happening in its legal area of competence. Said model diversifies the reception of criminal reports including in-person reports at Attorney General's Early Special Units for petty crime, ad hoc (in-site) reports for high-impact crimes, remote reports via internet or telephone, and Independent Unit reports. These reports then move to Mexico City's Attorney General's Office for police investigation, criminal analysis, and legal attention. Finally, certain cases move to local or federal courts as well as to special units for victim's protection. We include all crime reports, regardless of whether these move to court or not.

We measure the number of crimes per week per 100,000 inhabitants. Population data originates from the National Population Council (CONAPO). For our analysis, we exclusively use data from the 16 districts of Mexico City, from January to May of 2019 and 2020. This time selection provides a total of 22 weeks for each year. Mexico's government officially declared the stay-at-home order to start on March 23, 2020. However, Merodio-Gómez and Ramírez-Santiago (2020) present evidence that mobility in Mexico City began to decrease one week before the official stay-at-home order. Thus, we use the week before the government's official order as the excluded period in the event-study analysis.

Table 1 shows summary statistics for the 2019–2020 criminal activity in Mexico City. They are separated by conventional crime (domestic violence, burglary, robbery, vehicle theft, and assault-battery) and organized crime (kidnapping, extortion, and homicides). Among conventional crime, domestic violence has the highest rate with 5.40 cases per week per 100,000 inhabitants. Within organized crime, homicides present the highest rate with 0.25 cases per week per 100,000 inhabitants.

3.2. Methodology

To estimate the causal effect of COVID-19 on crime in Mexico City, we use a weekly event-study specification. Formally, this specification appears as:

$$Y_{mwt} = \sum_{q=-10}^{10} \beta_q Covid_{mq} + \alpha_m + \gamma_w + \mu_t + \varepsilon_{mwt}$$

where Y_{mwt} is the crime-rate outcome of interest for district m, in week w, in year t. $Covid_{mq}$ is a dummy variable that takes on the value of one for each period q surrounding the stay-at-home order for district (municipality) m. We use the 10 periods before and after the order, denoted as q. q represents the week relative to the stay-at-home order, which occurred at $q = 0$. We exclude week $q = -1$, which encompasses the week from March 9 to March 15 as the baseline period. The excluded baseline period also incorporates 2019 as a reference year for 2020. We additionally include district (municipality), week, and year fixed effects in the specification. α_m are district (municipality) fixed-effects which control for time-invariant differences across districts. γ_w are weekly fixed-effects to control for potential seasonal trends. μ_t are year fixed-effects to control for macroeconomic shocks, other than the pandemic. To correct for autocorrelation of the outcome—measured across weeks within the district—we apply clustered standard errors at the district level. The coefficients of interests are β_q.

Table 1
Descriptive statistics.

	Mean	Std. Dev.	50th Pct	Min	Max
Overall					
Crime Rate	16.223	7.278	15.228	0.718	43.637
Conventional					
Domestic Violence Rate	5.407	2.016	5.158	0.502	13.040
Burglary Rate	4.585	3.645	3.916	0.000	17.345
Robbery Rate	2.841	2.456	2.272	0.000	18.507
Vehicle Theft Rate	1.711	0.948	1.632	0.000	6.042
Assault-Battery Rate	1.078	0.645	1.016	0.000	4.199
Organized					
Homicides Rate	0.255	0.256	0.238	0.000	1.385
Kidnapping Rate	0.213	0.276	0.132	0.000	2.324
Extortion Rate	0.133	0.218	0.000	0.000	1.630
Observations	704				

SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Crime rates are measured per 100,000 inhabitants.

4. Results

4.1. Event-study findings

Fig. 2 shows the results for the event-study specification across the eight outcomes of interest. The plotted points show the COVID-19 stay-at-home order relative to the pre-period, $t = -1$. The first five panels in Fig. 2, and the first five columns in Table A.1, display conventional crime (e.g., domestic violence, burglary, robbery, vehicle theft, and assault-battery). The last three panels in Fig. 2 and the last three columns in Table A.1 present the findings for organized crime (kidnapping, extortion, and homicides).

The first panel displays the effect of the COVID-19 lockdown on domestic violence (Column 1 in Table A.1). In the weeks leading up to the stay-at-home order, the plotted points hover around zero and then begin to decline following the stay-at-home order. We also observe a decrease in crimes related to burglary (see the second panel of Fig. 2 and Column 2 in Table A.1). Both burglary and IPV decline by roughly two to three crimes per 100,000 inhabitants. The third panel of Fig. 2 presents the findings for robbery (Columns 3 in Table A.1). Robbery does not change in the ten weeks after the lockdown. For vehicle theft, included in the fourth panel of Fig. 2 (Column 4 in Table A.1), there is a sharp decrease from week five onwards. The magnitude of the decline is around 0.5 crimes prevented per 100,000 inhabitants. The fifth panel contains evidence for assault-battery. Assault-battery declines by between 0.5 and 1 crime per 100,000 inhabitants and is statistically significant after week two (Column 5 in Table A.1).

To better understand the size of the effects relative to the mean crime levels, we compare the declines to the control period in percentage terms. Week ten of the COVID-19 pandemic shows a decrease of 4.9 domestic violence reports per 100,000 inhabitants for the last week of our analysis (week 10). This reduction is 77% lower than the control period in 2020. Burglary, in week six, is reduced by 3.0 reports per 100,000 inhabitants. This drop accounts for 69% of the average incidents during the weeks before the stay-at-home order. Vehicle theft reports are lowest in week nine and reflect a 58% drop in reports per 100,000 inhabitants. Assault-battery is the lowest in week five and reflects a 70% decline relative to the base- line. These declines in crime rates reveal a more substantial effect as the stay-at-home orders continued.

Our findings for conventional crime both align with a portion of the existing literature but diverge from other previous findings. For burglary and assault-battery, our findings confirm the published results for the UK (Halford et al., 2020), Vancouver (Hodgkinson and Andresen, 2020), Los Angeles, and Indianapolis (Mohler et al., 2020). On the other hand, the domestic violence and vehicle theft findings coincide with results for the UK (Halford et al., 2020) but contrast with the evidence for Los Angeles, Indianapolis (Mohler et al., 2020), and Vancouver (Hodgkinson and Andresen, 2020). Robbery which we observe as stagnant, contradicts the previous findings in Halford et al. (2020) and Mohler et al. (2020).

For organized crime, the sixth panel of Fig. 2 presents the findings for homicides (Columns 6 in Table A.1). The results show no impact on homicides after the lockdown. Similarly, the seventh panel of Fig. 2 indicates no impact on kidnapping after the stay-at-home order. (Columns 7 Table A.1). Finally, extortion is stagnant over the first seven weeks, then declines for weeks eight and ten. These findings suggest that organized criminals continued to operate even under the pandemic and the stay-at-home orders in Mexico City.

4.2. Alternative specifications

We test seven alternatives to our primary specification as checks on the main event study. These tests include: (1) implementing a difference-in-difference approach, (2) grouping the pre-period in the event-study specification, (3) adding district (municipality)-specific weekly linear trends to the grouped pre-period, (4) including municipality-level population weights, (5) running a wild-cluster bootstrap standard error procedure, (6) applying a correction for multiple hypothesis testing, and (7) setting a placebo test. All checks verify the findings from the main specification.

First, we present alternative results with a difference-in-differences approach in Table 2. Panel A shows the results from the main specification grouped by pre-period (Eq. 1 $q = -10$ through $q = -1$) and post-period (Eq. 1 $q = 0$ through $q = 10$). We also include a district (municipality) specific linear time trend as well as the original weekly, yearly, and municipality-level fixed effects. The reported coefficient in Table 2 shows the post-period after the stay-at-home order went into effect. The coefficients reflect similar results to the main event study, where crime declines for all conventional measures, but only for extortion in organized crime. The difference-in-differences results reflect the average effect over the post-period in Fig. 2.

Second, in panel B of Table 2 we present the grouped pre-period (Eq. 1 $q = -10$ through $q = -1$). The results in this panel show the coefficients on the post weeks (zero through 10). We do not include time trends in the plotted points shown in Panel B, but Figs. A.1 and A.2 indicate similar results with time trends. The results with the grouped pre-period again align with the main findings in Fig. 2. The clearest declines in crime are for IPV and burglary. The remainder of conventional crimes, including assault, vehicle theft, and robbery, also fall, but indicate a less stark decline than IPV and burglary. Organized crimes show no evidence of a drop.

Third, in Figs. A.1 and A.2 we present the grouped pre-period from Panel B of Table 2, but add municipality-specific weekly linear trends. We overlay the results with the original baseline coefficients (in blue triangles), which allows for easy comparison of the robustness checks. The grouped pre-period specification with linear trends (in purple squares) is similar to the original point estimates (in blue triangles). The interpretation of the results is unchanged. Changing the specification to include the group pre and post-periods, the grouped pre-period, as well as the grouped pre-period with a time trend, all show similar patterns to the main results.

Fourth, we add weights for the district (municipality) size. We make this correction to address the fact that smaller districts will have higher variance in the crime rate from week- to-week than the larger districts. The plotted points in green circles appear nearly identical to the main results plotted in blue triangles. Adjusting the main specification with population weights again has little impact on the interpretation of the findings.

Fifth, we modify our main specification by using wild cluster standard errors. Cameron et al. (2008) suggests that standard errors are downward-biased with a low number of clusters (five to 30). Given that we have 16 clusters at the district (municipality) level, we conduct a wild cluster bootstrap procedure, as described in Cameron et al. (2008). Table A.2 reproduces the results of Table A.1 using a wild cluster bootstrap procedure to calculate standard errors. Under this method, Table A.2 shows that all coefficients remain statistically significant.

Six, in order to reduce the likelihood of false rejections, we conduct a correction for multiple testing using sharpened False Discovery Rate (FDR) q-values (Anderson, 2008). The results appear in Table A.3 where the *p*-values are presented in parenthesis and the sharpened q- values in brackets. We observe that, in general, the q-values are larger than the p-values. Yet, most of the coefficients that were statistically significant using p-values, remain statistically significant when using q-values.

Finally, Fig. A.3 presents results using a placebo test. For this check, we assume the lockdown occurred in 2019 instead of 2020 and compare 2019 to 2018 in an event study. The specification reflects Eq. 1, effectively replacing 2020 with 2019 and 2019 with 2018. The placebo test should show no reduction in crime unless there is unexpected seasonality or other confounding factors that we could not address in our baseline specification. As expected, most of the coefficients remained statistically insignificant after the placebo stay-at-home order. The only

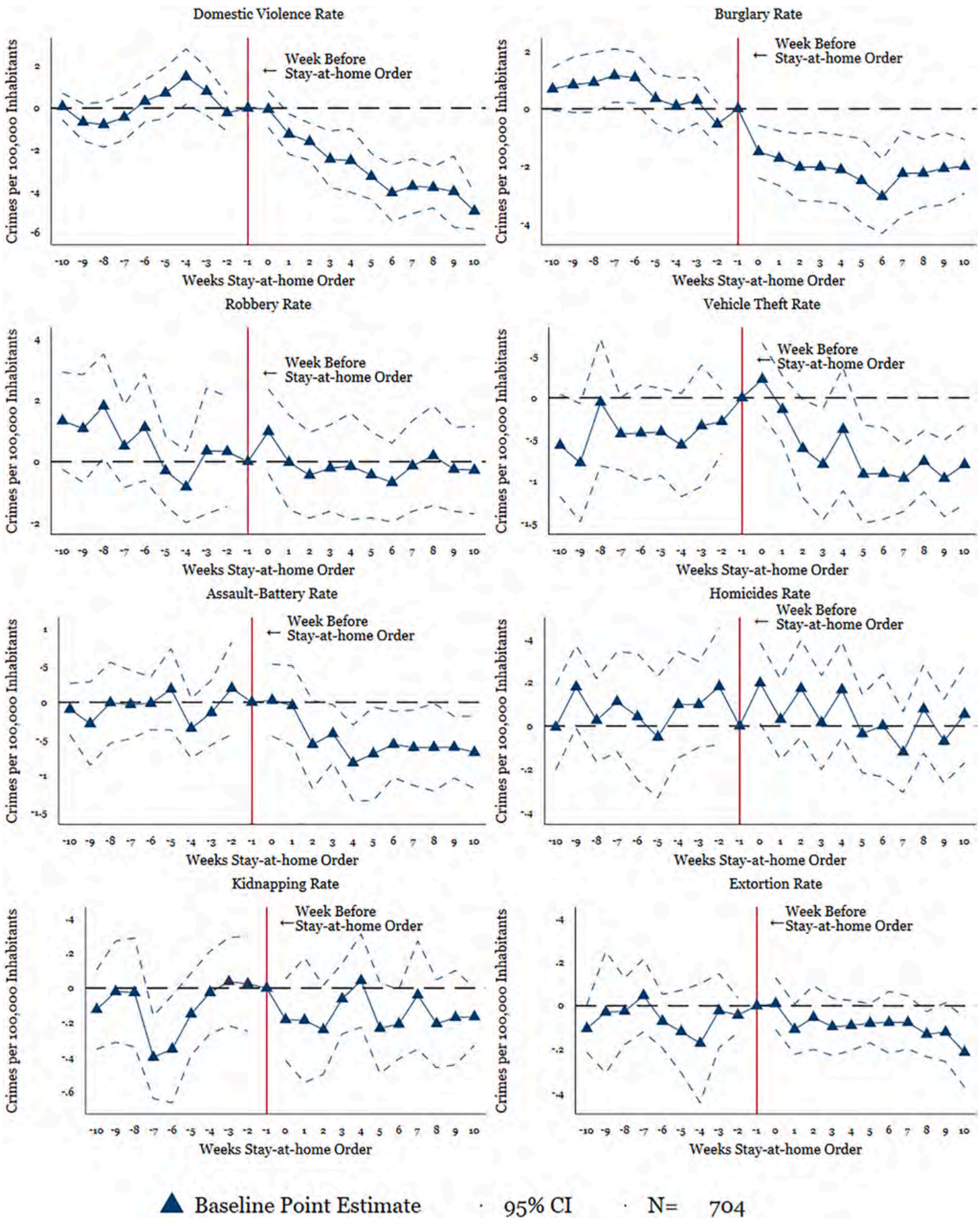

Fig. 2. Event study: main findings.
SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Plotted coefficients are event-study dummy variables, βq, from Equation 1. Each plotted point represents the number of weeks before and after the lockdown, excluding the period just before adoption. Solid lines represent point estimates. Dashed and dotted lines display the 95 percent confidence intervals. Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Crime rates are measured per 100,000 inhabitants.

Table 2
Difference-in-differences and grouped event study.

Panel A: difference-in-differences

	IPV	Bur glary	Robbery	Vehicle-Theft	Assault	Homicides	Kidnappings	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post x COVID-19	−3.27***	−2.54***	−0.88***	−0.37***	−0.51***	-0.04	−0.03	−0.05**
	(0.31)	(0.50)	(0.25)	(0.10)	(0.13)	(0.04)	(0.05)	(0.02)
Baseline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	704	704	704	704
Adjusted R-sq.	0.51	0.88	0.80	0.55	0.32	0.17	0.22	0.32
Mean Dependent	5.41	4.58	2.84	1.71	1.08	0.25	0.21	0.13

Panel B: grouped pre-period

	IPV	Burglary	Robbery	Vehicle-Theft	Assault	Homicides	Kidnappings	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week 0	−0.18	−1.99***	0.37	0.62***	0.09	0.14*	−0.08	0.07
	(0.38)	(0.55)	(0.26)	(0.19)	(0.24)	(0.07)	(0.11)	(0.04)
Week 1	−1.37***	-2.22***	−0.63	0.26	0.01	−0.03	−0.08	−0.05
	(0.41)	(0.51)	(0.45)	(0.19)	(0.23)	(0.08)	(0.13)	(0.04)
Week 2	−1.73***	−2.54***	−1.05***	−0.20	−0.51*	0.11	−0.14	0.00
	(0.46)	(0.56)	(0.32)	(0.24)	(0.26)	(0.10)	(0.09)	(0.04)
Week 3	−2.57***	−2.52***	−0.82**	−0.39	−0.37**	−0.05	0.04	−0.04
	(0.63)	(0.64)	(0.30)	(0.24)	(0.16)	(0.09)	(0.03)	(0.05)
Week 4	−2.63***	−2.62***	−0.76*	0.02	−0.76***	0.11	0.15	−0.03
	(0.63)	(0.66)	(0.39)	(0.30)	(0.21)	(0.12)	(0.09)	(0.05)
Week 5	−3.40***	−3.00***	−1.04**	−0.51**	−0.64**	−0.10	−0.13**	−0.02
	(0.53)	(0.78)	(0.46)	(0.24)	(0.25)	(0.08)	(0.06)	(0.04)
Week 6	−4.19***	−3.55***	−1.29**	−0.50***	−0.51*	−0.06	−0.10	−0.02
	(0.63)	(0.62)	(0.52)	(0.17)	(0.25)	(0.06)	(0.09)	(0.07)
Week 7	−3.86***	−2.75***	−0.75*	−0.56**	−0.56**	−0.18*	0.06	−0.02
	(0.54)	(0.74)	(0.36)	(0.19)	(0.23)	(0.09)	(0.11)	(0.04)
Week 8	−3.92***	−2.74***	−0.42	−0.36**	−0.55*	0.02	−0.10	−0.07
	(0.42)	(0.59)	(0.29)	(0.16)	(0.28)	(0.05)	(0.07)	(0.05)
Week 9	−4.12***	−2.58***	−0.86**	−0.56**	−0.55***	−0.13**	−0.06	−0.06
	(0.75)	(0.64)	(0.31)	(0.20)	(0.16)	(0.06)	(0.09)	(0.05)
Week 10	−5.06***	−2.50***	−0.89**	−0.40*	−0.62***	−0.01	−0.06	−0.16*
	(0.55)	(0.49)	(0.34)	(0.20)	(0.17)	(0.08)	(0.08)	(0.07)
Baseline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	704	704	704	704
Adjusted R-sq.	0.54	0.88	0.79	0.56	0.32	0.18	0.22	0.31
Mean Dependent	5.41	4.58	2.84	1.71	1.08	0.25	0.21	0.13

SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Panel A shows the difference-in-differences estimates, which group the pre-period (before week -1) and post periods (weeks zero through 10). We include time trends in the difference-indifferences specification. Panel B shows the results with the grouped pre-period findings, which excludes all weeks before week 0. The coefficients above reflect the post weeks zero through 10. For grouped pre-period results with time trends see Figs A.1 and A.2. Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Crime rates are measured per 100,000 inhabitants.

variable that did not pass this placebo test is assault-battery, which increases after the placebo stay-at-home order.

5. Discussion

Our findings have several implications for public policy. First, in the case of conventional crime, lockdowns do have an impact on criminals' behavior. These criminals may fear possible contagion. Also, as opposed to other types of natural events, a pandemic leaves little chance for opportunistic behavior by criminals as routine activities change. Potential victims stay at home and have less exposure to others, including criminals. Therefore, as in other cities and countries around the world, we find a general reduction of conventional crime in Mexico City. One exceptional case is domestic violence, which researches propose could increase under lockdown. Criminals and victims who spend more time under the same roof have more encounters that could arise into violence. Silverio-Murillo, Hoehn-Velasco, & Balmori de la Miyar, 2020, using data from a public call center in Mexico City and variation in alcohol-sales prohibition, show that calls of intimate partner violence asking for psychological help increases during the first months of the stay-at-home order. We interpret these results to suggest that the reported domestic violence is due to the criminal being confined with the victim, rather than an actual decline in domestic violence victimization. However, this is not the case for the rest of the crimes examined (e.g., burglary, vehicle theft, and assault-battery), in which the offender does not remain at the crime scene.

Another possible explanation for the drop in conventional crime is the deployment of the National Guard in Mexico City. As many police officers became infected with COVID-19, the Mayor of Mexico City asked for more than 2000 military personnel in the city to make up for the police officers affected by the virus (EFE, 2020). However, there is no evidence of an additional number of officers deployed. Therefore, we interpret the findings to show that the drop in crime has to do with criminal behavior rather than additional forces, as in other parts of the world.

Second and foremost, for policy purposes, our findings show that organized criminals continue to expand their influence in Mexico and, worse yet, use this exceptional circumstance to build up support from specific segments of the population by providing COVID-19 assistance in the form of food handouts (Felbab-Brown, 2020). These sorts of actions by criminal groups can be very profitable and are frequently employed by other mafias in the world like the Yakuza in Japan or the Sicilian mafia in Italy (Felbab-Brown, 2020). However, we have yet to see whether these sorts of actions will find sympathy within the population at large.

One point is clear, organized crime will have a fertile field in Mexico to recruit new gang members as youth unemployment is at an all-time high. The pandemic has produced a tremendous economic and social cost and resulted in the most substantial economic downturn in history in the Latin America region. In 2020, Mexico and Latin America GDP will decline by 9.0% and 9.1% (ECLAC, 2020). Extreme poverty in Mexico will rise from 11.1% to 17.4%, while the share of Mexicans in poverty will go up from 41.9% to 49.5 percent (ECLAC, 2020). Under this adverse economic scenario, once a vaccine becomes available, we expect conventional crime to resume and organized crime to increase even more.

If this comes true, it could jeopardize the Mexican government's main functions and turn this social situation into a national security issue. For instance, right in the middle of the stay-at-home order, one of the most powerful drug-trafficking organizations in Mexico, Jalisco New Generation Cartel, ambushed Mexico City's police chief, wounding him, while killing two of his bodyguards (Kitroeff, 2020). This same cartel was also involved in the murder of a judge and his wife two weeks earlier in a different part of Mexico (Kitroeff, 2020). Such high-profile government officials will be threatened more than ever unless the government makes extraordinary investments in criminal justice and the promotion of the rule of law. Right now, Mexico spends 0.5% of its GDP on public safety, the lowest among the OECD group, which spends three-times that of Mexico's, on average (Izquierdo et al., 2018). In fact, Mexico lags in public safety spending even within the Latin America region (Izquierdo et al., 2018).

6. Conclusion

In response to the COVID-19 pandemic, governments around the world imposed a lock-down to contain the health crisis and maintain hospitals at less-than-capacity. This health policy brought a series of economic and social consequences: some positive and some negative. Among the negative is the most substantial economic downturn in many regions of the world, including Latin America. On the positive side, many countries experienced a reduction in certain types of crime.

This paper studies the effect of the stay-at-home order on crime in Mexico City. We explore five different types of conventional crime and three other crimes related to organized crime. To do so, we employ an event study and a series of robustness tests that confirm our findings. Results show (1) a sharp decrease on crimes related to domestic violence, burglary, and vehicle theft; (2) a decrease in assault-battery and extortion crimes (only for certain weeks); and (3) no effects on crimes related to robbery, kidnapping, and homicides. These findings imply that conventional crime declines, while organized crime maintains similar activity levels during the pandemic. We expect that after the end of the pandemic, the havoc wrought in terms of economic and social costs will escalate crime in Mexico City back to its original levels. Worse yet, we expect that as youth unemployment reaches all-time highs, organized crime will proliferate, unless the government actively seeks to prevent it.

Declaration of Competing Interest

None.

Appendix A. Appendix

Table A.1
Event study: crime rate by type.

	IPV	Burglary	Robbery	Vehicle-Theft	Assault	Homicides	Kidnappings	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week −10	0.07	0.69*	1.33	−0.57*	−0.09	−0.01	−0.12	−0.10*
	(0.33)	(0.38)	(0.81)	(0.31)	(0.18)	(0.10)	(0.12)	(0.06)
Week −9	−0.68	0.83	1.08	−0.78**	−0.29	0.18*	−0.02	−0.03
	(0.45)	(0.49)	(0.89)	(0.36)	(0.29)	(0.10)	(0.15)	(0.14)
Week −8	−0.79	0.92	1.81*	−0.05	−0.01	0.03	−0.03	−0.03
	(0.55)	(0.53)	(0.86)	(0.39)	(0.28)	(0.10)	(0.16)	(0.08)
Week −7	−0.44	1.16**	0.50	−0.43*	−0.03	0.11	−0.40***	0.05
	(0.56)	(0.47)	(0.69)	(0.22)	(0.24)	(0.12)	(0.12)	(0.09)
Week −6	0.34	1.08**	1.12	−0.42	−0.01	0.04	−0.35**	−0.07
	(0.51)	(0.45)	(0.89)	(0.29)	(0.18)	(0.15)	(0.16)	(0.06)
Week −5	0.73	0.35	−0.30	−0.41	0.18	−0.05	−0.15	−0.12
	(0.62)	(0.44)	(0.58)	(0.27)	(0.28)	(0.14)	(0.12)	(0.10)
Week −4	1.50**	0.10	−0.82	−0.57*	−0.35	0.10	−0.03	−0.17
	(0.68)	(0.49)	(0.59)	(0.32)	(0.21)	(0.12)	(0.12)	(0.14)
Week −3	0.81	0.30	0.35	−0.34	−0.14	0.10	0.04	−0.02
	(0.59)	(0.40)	(1.04)	(0.37)	(0.22)	(0.10)	(0.13)	(0.09)
Week −2	−0.23	−0.53	0.33	−0.29	0.19	0.18	0.02	−0.04
	(0.45)	(0.37)	(0.91)	(0.20)	(0.32)	(0.14)	(0.14)	(0.04)
Week 0	−0.05	−1.49***	0.99	0.22	0.03	0.20*	−0.18	0.01
	(0.45)	(0.47)	(0.70)	(0.22)	(0.25)	(0.09)	(0.12)	(0.06)
Week 1	−1.25**	−1.71***	−0.02	−0.14	−0.05	0.03	−0.18	−0.11*
	(0.49)	(0.48)	(0.78)	(0.20)	(0.28)	(0.09)	(0.18)	(0.06)

SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Crime rates are measured per 100,000 inhabitants.

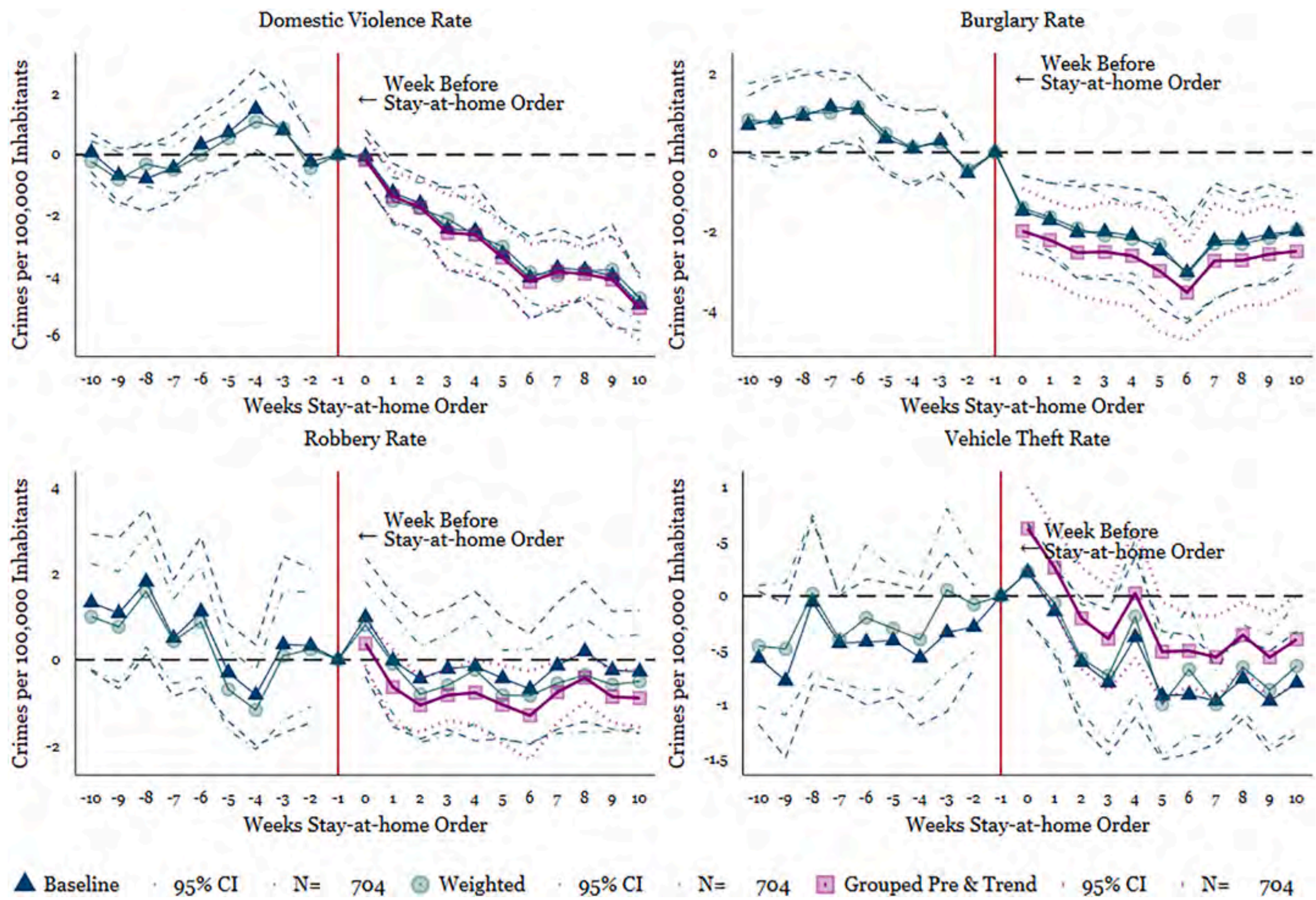

Fig. A.1. Event study: robustness of main findings i.

SOURCE: Mexico City's Attorney General's Office Administrative Data.

NOTES: The blue triangles reflect the baseline specification from Equation 1. The green circles show the plotted points with district-specific weights. The purple squares show the results from the specification with the grouped pre-period and reflect the post-period: weeks zero through 10. The grouped pre-period groups all periods before week zero and includes a linear district-specific weekly trend. Plotted coefficients are event-study dummy variables, βq, from Equation 1. Each plotted point represents the number of weeks before and after the lockdown, excluding the period just before adoption. Solid lines represent point estimates. Dashed and dotted lines display the 95 percent confidence intervals. Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Crime rates are measured per 100,000 inhabitants.

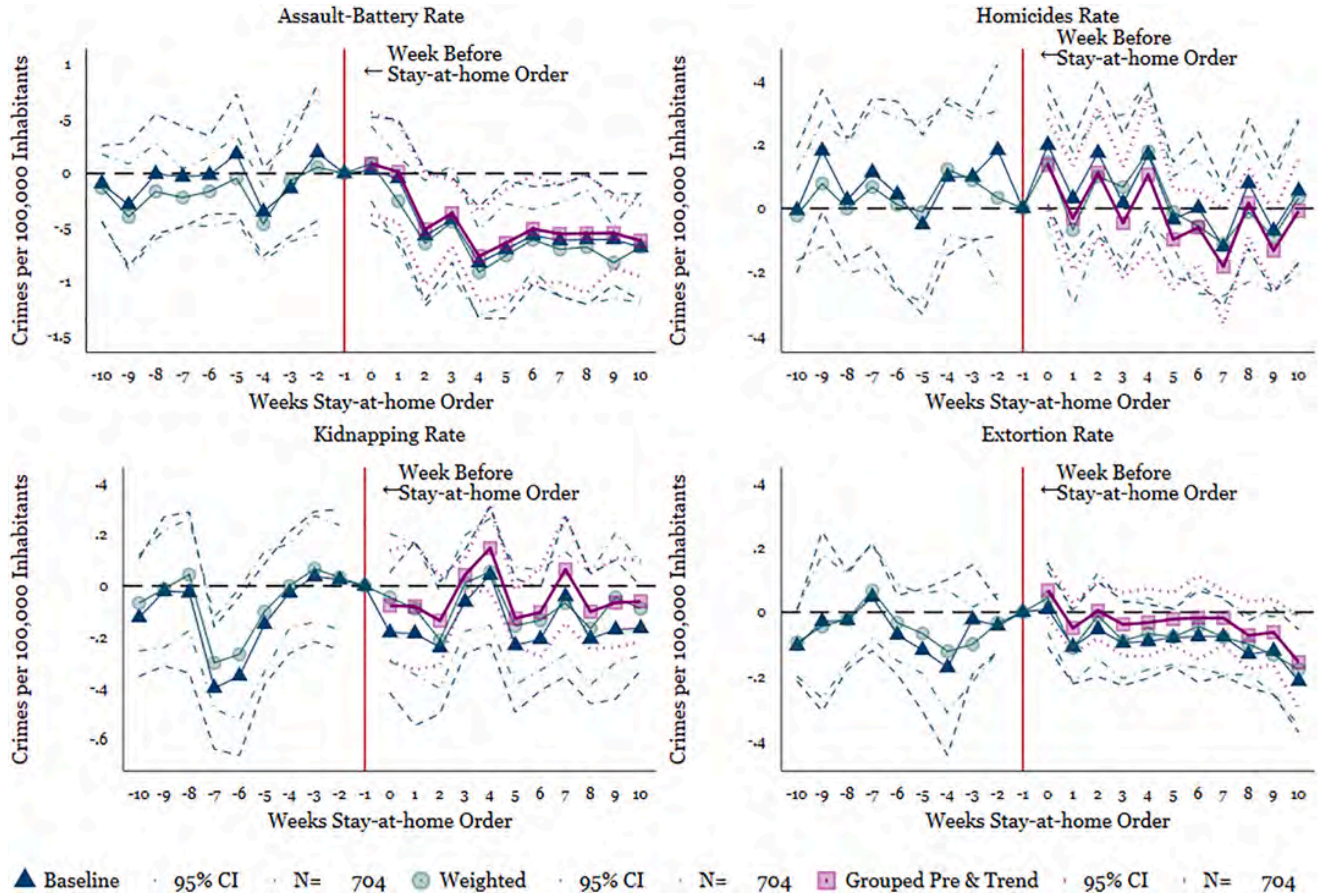

Fig. A.2. Event Study: Robustness of Main Findings 2.
SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: The blue triangles reflect the baseline specification from Equation 1. The green circles show the plotted points with district-specific weights. The purple squares show the results from the specification with the grouped pre-period and reflect the post-period: weeks zero through 10. The grouped pre-period groups all periods before week zero and includes a linear district-specific weekly trend. Plotted coefficients are event-study dummy variables, βq, from Equation 1. Each plotted point represents the number of weeks before and after the lockdown, excluding the period just before adoption. Solid lines represent point estimates. Dashed and dotted lines display the 95 percent confidence intervals. Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Crime rates are measured per 100,000 inhabitants.

Table A.2
Robustness: bootstrap standard errors.

	Domestic Violence	Burglary	Robbery	Vehicle Theft	Assault-Battery	Homicides	Kidnapping	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week −10	0.074	0.691*	1.329	−0.571*	−0.093	−0.006	−0.123	−0.104*
	[−0.5932, 0.7133]	[−0.03757, 1.461]	[−0.1554, 3.008]	[−1.206, 0.07839]	[−0.4621, 0.2743]	[−0.2236, 0.2014]	[−0.3355, 0.1255]	[−0.217, 0.008787]
Week −9	−0.677	0.835	1.079	−0.779**	−0.289	0.180*	−0.021	−0.029
	[−1.663, 0.2799]	[−0.2209, 1.839]	[−0.721, 2.991]	[−1.548, −0.0359]	[−0.9272, 0.3493]	[−0.01409, 0.389]	[−0.3162, 0.2939]	[−0.3138, 0.2691]
Week −8	−0.791	0.917	1.810*	−0.055	−0.006	0.026	−0.025	−0.026
	[−1.972, 0.2531]	[−0.2362, 1.992]	[0.1349, 3.667]	[−0.8456, 0.7827]	[−0.6125, 0.586]	[−0.1912, 0.2296]	[−0.3562, 0.3258]	[−0.1935, 0.1425]
Week −7	−0.437	1.157**	0.504	−0.434*	−0.031	0.112	−0.397***	0.048
	[−1.586, 0.6549]	[0.2163, 2.074]	[−0.7605, 1.935]	[−0.8762, 0.01912]	[−0.4985, 0.4878]	[−0.1362, 0.3592]	[−0.6389, −0.1458]	[−0.119, 0.2217]
Week −6	0.335	1.080**	1.118	−0.423	−0.014	0.043	−0.350**	−0.071
	[−0.6905, 1.457]	[0.08785, 1.974]	[−0.4779, 2.986]	[−1.026, 0.1735]	[−0.3958, 0.382]	[−0.287, 0.3454]	[−0.6582, −0.02566]	[−0.1991, 0.05278]
Week −5	0.727	0.352	−0.296	−0.410	0.177	−0.051	−0.149	−0.118
	[−0.5523, 2.043]	[−0.5536, 1.301]	[−1.374, 0.9077]	[−0.9599, 0.1326]	[−0.4047, 0.766]	[−0.3551, 0.2446]	[−0.3933, 0.1048]	[−0.3151, 0.07389]
Week −4	1.504**	0.099	−0.818	−0.567*	−0.353	0.099	−0.026	−0.172

(continued on next page)

Table A.2 (*continued*)

	Domestic Violence	Burglary	Robbery	Vehicle Theft	Assault-Battery	Homicides	Kidnapping	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[0.1053, 2.938]	[−0.9317, 1.03]	[−2.011, 0.4023]	[−1.235, 0.06217]	[−0.7784, 0.08696]	[−0.1718, 0.3695]	[−0.2747, 0.2412]	[−0.4492, 0.09605]
Week −3	0.805	0.296	0.350	−0.337	−0.139	0.099	0.037	−0.023
	[−0.3757, 2.01]	[−0.5409, 1.111]	[−1.563, 2.551]	[−1.093, 0.4282]	[−0.6072, 0.3203]	[−0.1044, 0.3083]	[−0.2185, 0.3081]	[−0.2021, 0.1618]
Week −2	−0.229	−0.531	0.330	−0.285	0.189	0.181	0.024	−0.043
	[−1.137, 0.6804]	[−1.333, 0.2052]	[−1.49, 2.352]	[−0.6912, 0.119]	[−0.4828, 0.8767]	[−0.1002, 0.4577]	[−0.2032, 0.313]	[−0.1266, 0.03682]
Week 0	−0.054	−1.486***	0.986	0.220	0.029	0.198*	−0.182	0.010
	[−0.9361, 0.8187]	[−2.47, −0.5748]	[−0.2471, 2.495]	[−0.2375, 0.6694]	[−0.5025, 0.5344]	[0.0001, 0.3928]	[−0.4315, 0.07563]	[−0.1164, 0.141]
Week 1	−1.247**	−1.715***	−0.020	−0.140	−0.046	0.031	−0.185	−0.107*
	[−2.243, −0.2317]	[−2.741, −0.7635]	[−1.442, 1.632]	[−0.5497, 0.2854]	[−0.61, 0.5122]	[−0.1541, 0.2263]	[−0.5591, 0.1767]	[−0.2273, 0.01285]
Week 2	−1.606***	−2.031***	−0.439	−0.608*	−0.572*	0.173	−0.240*	−0.054
	[−2.559, −0.6676]	[−3.342, −0.8681]	[−1.907, 1.046]	[−1.224, −0.007608]	[−1.242, 0.004914]	[−0.05679, 0.4186]	[−0.5092, 0.0156]	[−0.2117, 0.09928]
Week 3	−2.447***	−2.013***	−0.207	−0.796**	−0.425*	0.016	−0.061	−0.096
	[−3.985, −0.9937]	[−3.284, −0.7269]	[−1.467, 1.262]	[−1.478, −0.07094]	[−0.8422, −0.01105]	[−0.2234, 0.2506]	[−0.2544, 0.1489]	[−0.2361, 0.03565]
Week 4	−2.509***	−2.112***	−0.149	−0.379	−0.821***	0.167	0.043	−0.090
	[−4.174, −0.9825]	[−3.377, −0.8489]	[−1.773, 1.553]	[−1.123, 0.3514]	[−1.354, −0.3042]	[−0.06457, 0.4025]	[−0.245, 0.3246]	[−0.208, 0.02788]
Week 5	−3.271***	−2.494***	−0.429	−0.915***	−0.699**	−0.035	−0.231	−0.080
	[−4.491, −2.106]	[−4.039, −1.096]	[−1.694, 1.071]	[−1.539, −0.3242]	[−1.372, −0.009763]	[−0.2373, 0.1628]	[−0.4946, 0.03808]	[−0.1798, 0.0009479]
Week 6	−4.060***	−3.041***	−0.678	−0.907***	−0.570**	0.002	−0.207*	−0.076
	[−5.492, −2.664]	[−4.456, −1.658]	[−2.021, 0.6574]	[−1.464, −0.3543]	[−1.034, −0.09424]	[−0.2495, 0.2589]	[−0.4121, 0.0004872]	[−0.2281, 0.06903]
Week 7	−3.738***	−2.242**	−0.136	−0.965***	−0.615**	−0.120	−0.040	−0.076
	[−5.106, −2.327]	[−3.807, −0.7342]	[−1.505, 1.442]	[−1.374, −0.5423]	[−1.115, −0.06137]	[−0.303, 0.08329]	[−0.3683, 0.2659]	[−0.2131, 0.05392]
Week 8	−3.799***	−2.228***	0.197	−0.762***	−0.610*	0.078	−0.205	−0.130**
	[−4.792, −2.779]	[−3.483, −1.009]	[−1.401, 1.815]	[−1.126, −0.37]	[−1.278, 0.01535]	[−0.1342, 0.2902]	[−0.4638, 0.05974]	[−0.2388, −0.02618]
Week 9	−3.995***	−2.070***	−0.244	−0.966***	−0.608**	−0.070	−0.169	−0.120
	[−5.708, −2.195]	[−3.356, −0.7174]	[−1.461, 1.202]	[−1.464, −0.4677]	[−1.025, −0.1869]	[−0.2664, 0.1263]	[−0.4516, 0.09145]	[−0.2779, 0.02229]
Week 10	−4.932***	−1.997***	−0.275	−0.801***	−0.678**	0.054	−0.165*	−0.213**
	[−5.832, −3.983]	[−2.953, −1.005]	[−1.624, 1.297]	[−1.322, −0.3048]	[−1.195, −0.1502]	[−0.1888, 0.2883]	[−0.336, 0.008119]	[−0.3926, −0.05467]
Baseline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	704	704	704	704
R^2	0.57	0.80	0.73	0.55	0.36	0.24	0.26	0.34

SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Baseline fixed effects are included at the district (municipality), week, and year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Crime rates are measured per 100,000 inhabitants. Wild-cluster bootstrap standard errors in brackets.

Table A.3
Robustness: multiple hypothesis testing.

	Domestic Violence	Burglary	Robbery	Vehicle Theft	Assault-Battery	Homicides	Kidnapping	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Week −10	0.07	0.69*	1.33	−0.57*	−0.09	−0.01	−0.12	−0.10*
	(0.825)	(0.092)	(0.125)	(0.091)	(0.614)	(0.956)	(0.314)	(0.083)
	[0.531]	[0.112]	[0.137]	[0.111]	[0.438]	[0.592]	[0.270]	[0.106]
Week −9	−0.68	0.83	1.08	−0.78**	−0.29	0.18*	−0.02	−0.03
	(0.160)	(0.112)	(0.251)	(0.050)	(0.335)	(0.087)	(0.892)	(0.844)
	[0.165]	[0.127]	[0.227]	[0.070]	[0.283]	[0.108]	[0.560]	[0.538]
Week −8	−0.79	0.92	1.81*	−0.05	−0.01	0.03	−0.03	−0.03
	(0.175)	(0.106)	(0.055)	(0.891)	(0.983)	(0.794)	(0.878)	(0.750)
	[0.178]	[0.123]	[0.076]	[0.560]	[0.598]	[0.516]	[0.555]	[0.510]
Week −7	−0.44	1.16**	0.50	−0.43*	−0.03	0.11	−0.40***	0.05
	(0.454)	(0.028)	(0.479)	(0.073)	(0.898)	(0.361)	(0.005)	(0.589)
	[0.365]	[0.043]	[0.373]	[0.093]	[0.562]	[0.297]	[0.010]	[0.424]
Week −6	0.34	1.08**	1.12	−0.42	−0.01	0.04	−0.35**	−0.07
	(0.523)	(0.032)	(0.231)	(0.176)	(0.941)	(0.776)	(0.044)	(0.284)
	[0.395]	[0.048]	[0.214]	[0.178]	[0.584]	[0.516]	[0.064]	[0.250]
Week −5	0.73	0.35	−0.30	−0.41	0.18	−0.05	−0.15	−0.12
	(0.268)	(0.437)	(0.618)	(0.150)	(0.543)	(0.730)	(0.238)	(0.246)

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Table A.3 (*continued*)

	Domestic Violence	Burglary	Robbery	Vehicle Theft	Assault-Battery	Homicides	Kidnapping	Extortion
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[0.243]	[0.354]	[0.441]	[0.159]	[0.409]	[0.501]	[0.221]	[0.223]
Week −4	1.50**	0.10	−0.82	−0.57*	−0.35	0.10	−0.03	−0.17
	(0.044)	(0.845)	(0.193)	(0.096)	(0.112)	(0.448)	(0.838)	(0.241)
	[0.065]	[0.538]	[0.194]	[0.114]	[0.127]	[0.362]	[0.537]	[0.222]
Week −3	0.81	0.30	0.35	−0.34	−0.14	0.10	0.04	−0.02
	(0.195)	(0.479)	(0.745)	(0.384)	(0.548)	(0.347)	(0.783)	(0.800)
	[0.195]	[0.373]	[0.508]	[0.316]	[0.410]	[0.291]	[0.516]	[0.517]
Week −2	−0.23	−0.53	0.33	−0.29	0.19	0.18	0.02	−0.04
	(0.622)	(0.175)	(0.726)	(0.170)	(0.566)	(0.208)	(0.864)	(0.316)
	[0.441]	[0.178]	[0.501]	[0.173]	[0.416]	[0.203]	[0.552]	[0.271]
Week 0	−0.05	−1.49***	0.99	0.22	0.03	0.20*	−0.18	0.01
	(0.906)	(0.006)	(0.185)	(0.339)	(0.910)	(0.056)	(0.153)	(0.877)
	[0.562]	[0.012]	[0.185]	[0.284]	[0.564]	[0.076]	[0.161]	[0.555]
Week 1	−1.25**	−1.71***	−0.02	−0.14	−0.05	0.03	−0.18	−0.11*
	(0.024)	(0.003)	(0.981)	(0.508)	(0.872)	(0.751)	(0.334)	(0.090)
	[0.038]	[0.007]	[0.598]	[0.387]	[0.552]	[0.510]	[0.283]	[0.110]
Week 2	−1.61***	−2.03***	−0.44	−0.61*	−0.57*	0.17	−0.24*	−0.05
	(0.003)	(0.004)	(0.551)	(0.062)	(0.084)	(0.154)	(0.089)	(0.489)
	[0.007]	[0.008]	[0.411]	[0.084]	[0.106]	[0.161]	[0.110]	[0.377]
Week 3	−2.45***	−2.01***	−0.21	−0.80**	−0.43*	0.02	−0.06	−0.10
	(0.003)	(0.005)	(0.780)	(0.035)	(0.054)	(0.887)	(0.565)	(0.177)
	[0.007]	[0.010]	[0.516]	[0.053]	[0.074]	[0.559]	[0.416]	[0.178]
Week 4	−2.51***	−2.11***	−0.15	−0.38	−0.82***	0.17	0.04	−0.09
	(0.006)	(0.004)	(0.869)	(0.334)	(0.007)	(0.164)	(0.761)	(0.147)
	[0.011]	[0.008]	[0.552]	[0.283]	[0.013]	[0.169]	[0.516]	[0.157]
Week 5	−3.27***	−2.49***	−0.43	−0.92***	−0.70**	−0.04	−0.23	−0.08
	(0.001)	(0.005)	(0.561)	(0.009)	(0.049)	(0.709)	(0.106)	(0.107)
	[0.001]	[0.009]	[0.415]	[0.015]	[0.070]	[0.498]	[0.123]	[0.124]
Week 6	−4.06***	−3.04***	−0.68	−0.91***	−0.57**	0.00	−0.21*	−0.08
	(0.001)	(0.001)	(0.321)	(0.006)	(0.027)	(0.987)	(0.062)	(0.315)
	[0.001]	[0.001]	[0.274]	[0.011]	[0.042]	[0.600]	[0.084]	[0.270]
Week 7	−3.74***	−2.24**	−0.14	−0.96***	−0.62**	−0.12	−0.04	−0.08
	(0.001)	(0.010)	(0.860)	(0.001)	(0.034)	(0.232)	(0.806)	(0.244)
	[0.001]	[0.017]	[0.551]	[0.001]	[0.051]	[0.214]	[0.520]	[0.222]
Week 8	−3.80***	−2.23***	0.20	−0.76***	−0.61*	0.08	−0.20	−0.13**
	(0.001)	(0.002)	(0.818)	(0.001)	(0.065)	(0.465)	(0.137)	(0.027)
	[0.001]	[0.005]	[0.525]	[0.003]	[0.086]	[0.366]	[0.151]	[0.042]
Week 9	−4.00***	−2.07***	−0.24	−0.97***	−0.61**	−0.07	−0.17	−0.12
	(0.001)	(0.006)	(0.733)	(0.001)	(0.013)	(0.494)	(0.243)	(0.104)
	[0.001]	[0.011]	[0.501]	[0.003]	[0.022]	[0.378]	[0.222]	[0.122]
Week 10	−4.93***	−2.00***	−0.28	−0.80***	−0.68**	0.05	−0.16*	−0.21**
	(0.000)	(0.001)	(0.713)	(0.005)	(0.017)	(0.645)	(0.071)	(0.020)
	[0.001]	[0.002]	[0.498]	[0.010]	[0.027]	[0.453]	[0.091]	[0.032]
Baseline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	704	704	704	704	704	704	704	704
$R2$	0.57	0.80	0.73	0.55	0.36	0.24	0.26	0.34

SOURCE: Mexico City's Attorney General's Office Administrative Data.
NOTES: Baseline fixed effects are included at the district (municipality), week, and year. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Crime rates are measured per 100,000 inhabitants. P-values are in parenthesis and sharpened q-values are in brackets.

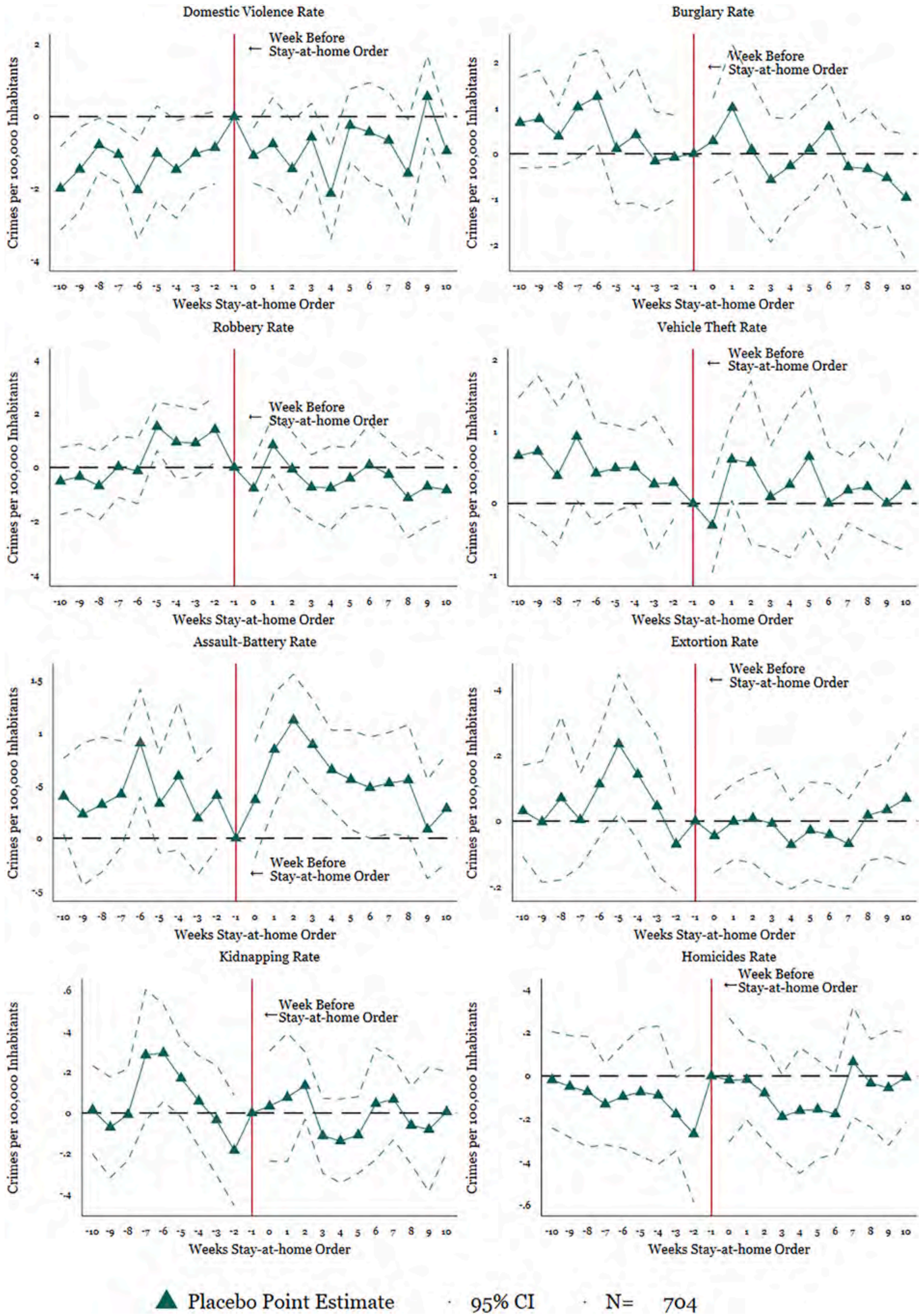

Fig. A.3. Robustness: event study using a placebo test.
SOURCE: Mexico City's Attorney General's Office Administrative Data.

NOTES: Plotted coefficients are event-study dummy variables, βq, from Equation 1. Each plotted point represents the number of weeks before and after the lockdown, excluding the period just before adoption. Solid lines represent point estimates. Dashed and dotted lines display the 95 percent confidence intervals. Baseline fixed effects are included at the district (municipality), week, and year. Robust standard errors are clustered at the district (municipality) level. Crime rates are measured per 100,000 inhabitants.

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