

Have US-Funded CARSI Programs Reduced Crime and Violence in Central America?

An Examination of LAPOP'S Impact Assessment of US Violence Prevention Programs in Central America

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Executive Summary

In October 2014, the Latin American Public Opinion Project (LAPOP) at Vanderbilt University published an impact assessment study of community-based violence prevention programs that have been implemented under the umbrella of the US State Department's Central American Regional Security Initiative (CARSI). The study looked at survey data measuring public perceptions of crime in 127 treatment and control neighborhoods in municipalities in El Salvador, Guatemala, Honduras, and Panama where the violence prevention programs have been implemented. The study's authors stated that the data shows that "in several key respects the programs have been a success" and note, for instance, that 51 percent fewer residents of "treated" communities reported being aware of murders and extortion incidents during the previous 12 months, and 19 percent fewer residents reported having heard about robberies having occurred.

As the LAPOP study is, to date, the only publicly accessible impact assessment of programs carried out under CARSI — a notoriously opaque regional assistance scheme that has received hundreds of millions of dollars of US government funding — a thorough review of the LAPOP study data seemed appropriate.

The following report examines the data collected during the LAPOP study and subjects them to a number of statistical tests. The authors find that the study cannot support the conclusion that the areas subject to treatment in the CARSI programs showed better results than those areas that were not.

This report identifies major problems with the LAPOP study, namely, the nonrandomness of the selection of treatment versus control areas and how the differences in initial conditions, as well as differences in results between treatment and control areas, have been interpreted. In the case of reported robberies, if the areas subject to treatment have an elevated level of reported robberies in the year prior to treatment, it is possible that there is some reversion to normal levels over the next year. The LAPOP methodology does not differentiate between effective treatment and, for example, an unrelated decline in reported robberies in a treated area following a year with an abnormally high number of reported robberies. The series of statistical tests in this report indicate that this possibility is quite plausible, and cannot be ruled out; and that the LAPOP study, therefore, does not demonstrate a statistically significant positive effect of treatment. The same can be said for the other variables where the LAPOP study finds significant improvement.

Introduction

In 2007, President George W. Bush created the Merida Initiative, a regional response to rising violence and drug trafficking in Mexico and Central America. In 2010, the Obama administration separated the Central American countries from the Merida Initiative with the creation of a new program known as the Central American Regional Security Initiative (CARSI). Between fiscal year 2008 and fiscal year 2015, the US appropriated at least \$1.2 billion of assistance to Central America through these two initiatives, according to the Congressional Research Service (CRS).¹

Following the large increase in migration from Central American countries, especially of unaccompanied minors in 2014, the US government proposed significantly increasing its expenditures in the region, with a focus on the Northern Triangle countries of Guatemala, Honduras, and El Salvador. Billed as a new form of assistance aimed at mitigating the dire economic conditions and extraordinarily high levels of violence in these three countries, the Obama administration's 2015 Strategy for Engagement in Central America greatly increases the budget for CARSI. For fiscal year 2016, \$349 million dollars has been allocated for CARSI, up from \$170 million in fiscal year 2015.²

The stated goals of CARSI are to assist law enforcement and security forces in dealing with drug trafficking, organized crime, and gang activity throughout the region; increase the capacity and accountability of the region's governments; and strengthen state and security apparatus presence in at-risk communities.³ Beyond these broad goals, relatively little is known about CARSI, since the US government has so far failed to publish detailed information on how the program's funds are being used in each country.

CARSI programs have increasingly come under fire, with human rights groups as well as members of Congress criticizing the US government for not doing enough to combat corruption and human rights abuses perpetrated by the region's increasingly militarized security forces.⁴ For several years, dozens of members of Congress have called for the complete suspension of security assistance to Honduras, one of the top recipients of CARSI aid, due to abuses — some documented, others alleged — by police and military forces and frequent killings of activists with impunity.

1 Meyer and Seelke (2015).

2 US House of Representatives Committee on Appropriations (2015).

3 US Department of State. "Central America Regional Security Initiative."

4 Main (2015).

There is little indication that the hundreds of millions of dollars that the US government has poured into CARSI have had a net positive impact. As CRS noted in a December 2015 report on CARSI, “most country-level security indicators have yet to show significant improvements.”⁵ Though the State Department’s Bureau of International Narcotics and Law Enforcement Affairs claims to be carrying out regular assessments of CARSI programs, it hasn’t published these assessments or revealed the metrics that it employs.⁶

To date, only one in-depth assessment of a CARSI program has been published. In October 2014, the Latin American Public Opinion Project (LAPOP) at Vanderbilt University published a study titled, “Impact Evaluation of USAID’s Community-Based Crime and Violence Prevention Approach in Central America: Regional Report for El Salvador, Guatemala, Honduras and Panama.”⁷ The study, conducted in 2013 with the support of the US Agency for International Development (USAID), seeks to assess the impact of CARSI-funded community based crime and violence prevention programs carried out by USAID in municipalities located in El Salvador, Guatemala, Honduras, and Panama. Though the State Department hasn’t specified how much funding these programs have received, itemized budgetary breakdowns in appropriations legislation show that USAID receives a relatively small proportion of the total funding provided for CARSI.

The LAPOP study’s findings — based on a survey of public perceptions of crime in both “treated” and “control” communities in the four countries — suggest that the prevention programs have been successful. For instance, according to the study, 51 percent fewer residents of “treated” communities reported being aware of murders and extortion incidents during the previous 12 months, and 19 percent fewer residents reported having heard about robberies having occurred. The results of the study have been frequently cited by the State Department and USAID as “evidence that these kinds of programs are working.”⁸

Given that this study is the only publicly available impact assessment of a CARSI program and is being used by the US government to justify continued and increased investment in CARSI, a thorough review of the LAPOP study seems appropriate.

The following report examines the data collected during the LAPOP study and subjects them to a number of statistical tests. The authors find that the study cannot support the conclusion that the areas subject to treatment in the CARSI programs showed better results than those areas that were not.

5 Meyer and Seelke (2015).

6 Ibid.

7 Berk-Seligson et al (2014).

8 Hogan (2014).

The main problem in the LAPOP study is the nonrandomness of the selection of treatment versus control areas, and how the differences in initial conditions, as well as differences in results between treatment and control areas, were interpreted. For example, in the case of reported robberies, if the areas subject to treatment have an elevated level of reported robberies in the year prior to treatment, it is possible that there is some reversion to normal levels over the next year. The LAPOP methodology does not differentiate between effective treatment and, for example, an unrelated decline in reported robberies in a treated area following a year with an abnormally high number of reported robberies. The series of statistical tests in this paper indicate that this possibility is quite plausible, and cannot be ruled out; and that the LAPOP study, therefore, does not demonstrate a statistically significant positive effect of treatment. The same can be said for the other variables where the LAPOP study finds significant improvement.

As a result, there is still no evidence that the CARSI program has produced positive results.

An Examination of the Data

This paper focuses on the data from the LAPOP survey question on robbery — the first indicator of interest to the study authors. The question asked to survey respondents in control and treatment areas in three rounds of surveys (pretreatment, midterm, and final) was: “Have robberies occurred over the last twelve months in [name of neighborhood]?”⁹ The study authors note: “Regionally, 19% fewer surveyed residents reported cases of robberies than would be expected without USAID intervention,” and “the greatest decrease in reported robberies can be found in Honduras, with 35% fewer cases of robberies being reported to the interviewer conducting the LAPOP survey.”¹⁰

An examination of the data, however, shows that the areas in the treatment group were — before any treatment — considerably different from the control areas. On average, respondents in areas scheduled for future treatment were 0 to 4 percentage points more likely than those in control areas to say they knew of robberies in the neighborhood during the previous 12 months.¹¹

After treatment, however, the respondents in the treated areas were 3 to 7 percentage points *less* likely to indicate that they were aware of robberies in their neighborhood. This seems to suggest that intervention, on average, reduced exposure to robbery among those in treated areas.

⁹ Berk-Seligson et al (2014), p. 32.

¹⁰ Ibid.

¹¹ See Appendix for the regression model, results, and more detail.

However, once country, municipality, and community random effects and controls for several socioeconomic indicators are included in the model, the process works differently. Once these controls were applied, the authors found that, in the pretreatment phase, those in areas to be treated were 4 to 12 percentage points more likely to report being aware of robberies than people in the control areas. In a close replication based on the available data, the difference, pretreatment, was 6 to 10 percentage points.

The fact that respondents in *pretreatment* control areas appear to be less prone to robbery than ones in areas to be treated — once geography and socioeconomic variables are accounted for — suggests that the areas selected for treatment may not be sufficiently similar to the control areas to safely conclude that the interventions helped.

With areas to be treated selected at random within municipalities, pretreatment survey results there ought to be similar to results in the control areas. Of course, researchers may get unlucky. With only a small number of areas surveyed in each municipality, the treatment and control groups may be quite different. For example, in Esquipulas, Guatemala, 32 percent of those surveyed pretreatment in areas to be treated said that they had heard of robberies in their neighborhood in the last 12 months; only 19 percent gave the same response in the control areas — a difference both economically and statistically significant.

Even after controlling for a number of socioeconomic factors, it is statistically unlikely that the rates of robbery reporting pretreatment were similar in treatment and control areas of the municipality. The authors observe a statistically significant difference in pretreatment rates of reported robberies in 11 of the 14 municipalities surveyed; in 8 of the 11, the treatment area reported more robberies than in the control area (see **Table 1**).

TABLE 1

Differences in Reported Robberies by Municipality		
	Number of Municipalities (Number of Respondents)	
	Treatment < Control	Treatment > Control
P<0.01	2 (1888)	5 (3523)
0.01<P<0.05	1 (576)	3 (1424)
0.05<P<0.1	0	1 (988)
P>0.1	2 (866)	0

Chi2 = 4.5, p=21%
Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

Though treated areas were not *as a group* statistically more likely to have respondents report robberies at higher rates, the sample size was particularly small. Fifty-five percent of *respondents* lived in municipalities where robbery reporting rates differed between treatment and control at the 1 percent level of statistical significance with another 23 percent below the 5 percent threshold.

How one interprets this kind of nonrandomness in the selection of areas for treatment may make a big difference in how the effects of treatment are modeled. If one considers a municipality where robbery reporting was higher in the treated area than in the control, this may be due to unlucky selection for treatment of fundamentally high-robbery areas. On the other hand, it may be unlucky not because treatment areas were fundamentally high-robbery, but merely because they happened in the previous year to have had a relatively high rate of robbery.

In the first case, a good baseline assumption would be that low-robbery control areas pretreatment will continue to be low-robbery areas after treatment. Thus, if after treatment, those surveyed in the high-robbery areas report robberies at rates closer to the control, then this reduction in crime may be attributed to the treatment.

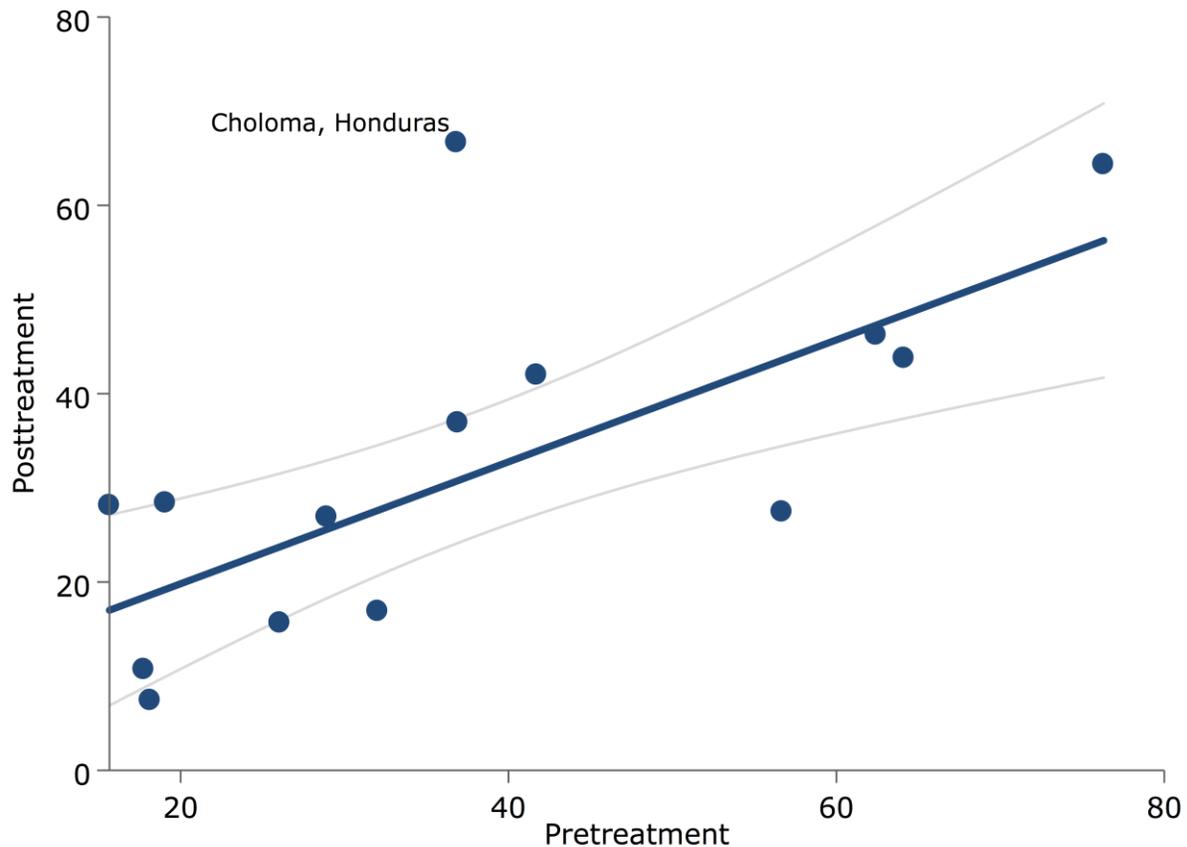
In the second case, where the areas selected for treatment have simply experienced a relatively high-robbery year, a good baseline assumption would be that high-robbery treatment areas will see their robbery reporting rates fall toward control. Because 69 percent of respondents lived in municipalities with elevated robbery in the areas to be treated, one would expect a natural fall in reported robberies relative to control areas.

Therefore, interpretation of a statistically significant fall in reported robberies in treated areas depends on how one accounts for the pretreatment difference in reported robbery rates relative to control areas. One way to distinguish between these accounts would be to investigate whether *control* areas with high robbery rates prior to treatment had relatively low rates in the posttreatment period, compared to control areas in other municipalities. Indeed, municipalities which had high *control* rates

of robbery reports pretreatment also had high *control* rates of robbery after treatment. This is seen in **Figure 1**.

FIGURE 1

Robbery Reports in Control Areas Before and After Intervening in Treatment Areas



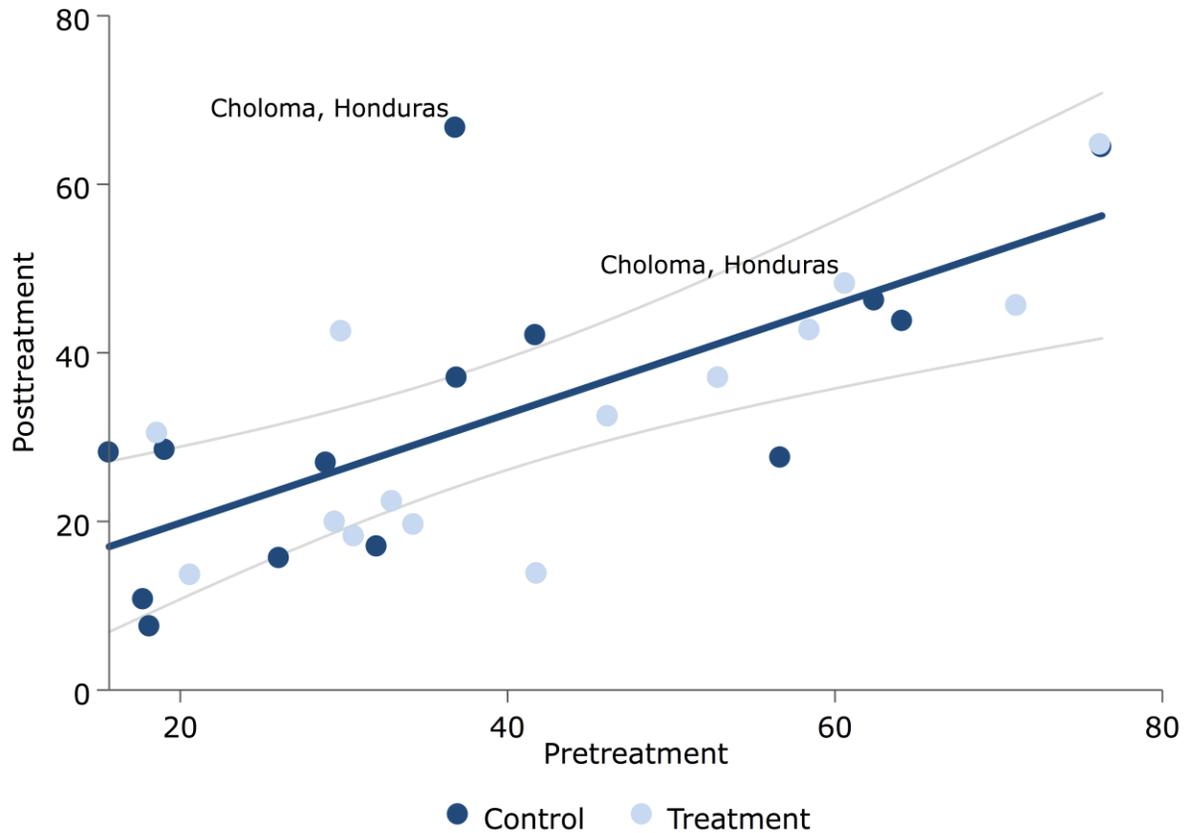
Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

Regression robust to outliers shows that every percentage point increase in the rate of reported robberies pretreatment in control areas is associated with an additional 0.25 to 1.0 percentage points after intervention (see Appendix). Note that the rate of reported robberies in control areas of Choloma, Honduras increased by an unusually large amount. Rather than falling from 37 percent to an expected 31 percent, as the regression would predict, the rate jumped to 67 percent.

Figure 2 is identical to Figure 1 except that the treatment areas have been added in lighter blue. The regression line is unchanged — still based solely on the control areas.

FIGURE 2

Robbery Reports Adding Treatment Areas Before and After Intervening



Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

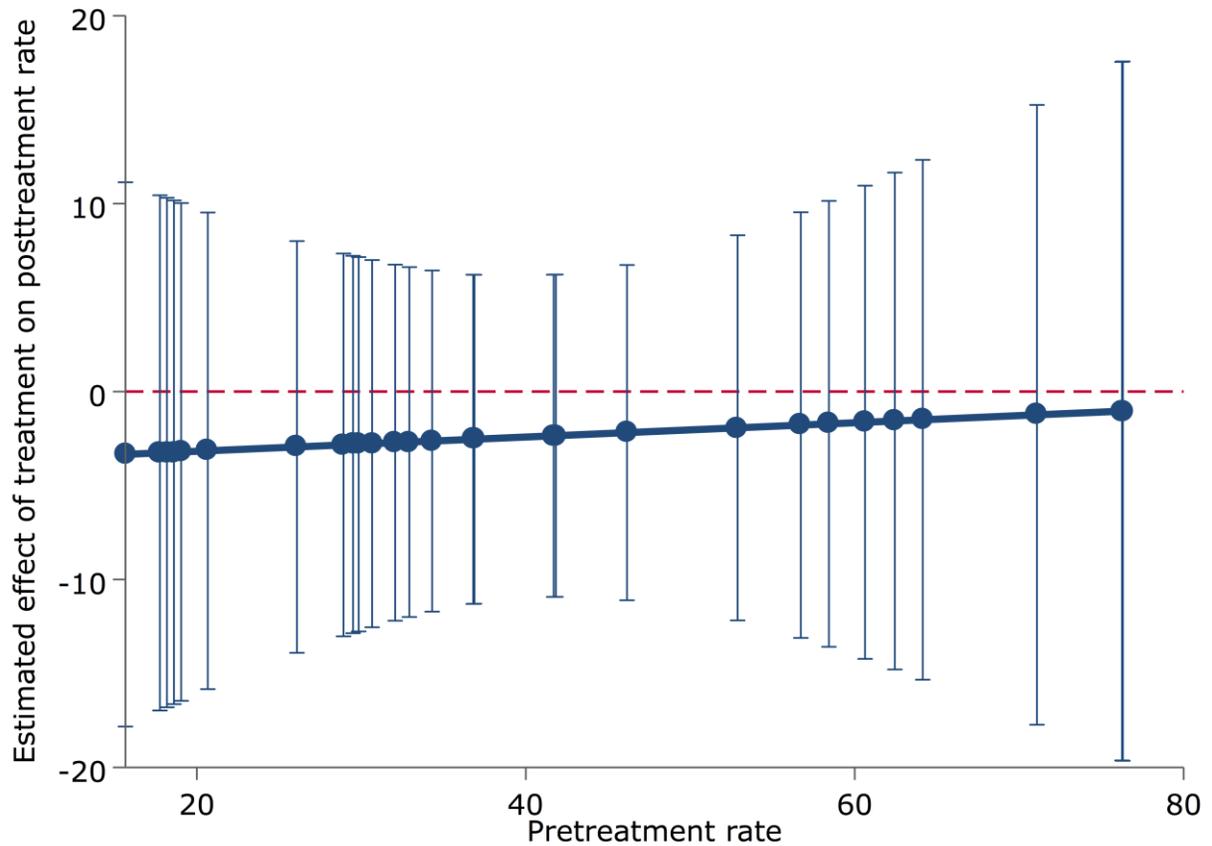
One can see that the relationship between pre- and posttreatment control areas does a good job of helping predict reported robberies in posttreatment areas of intervention.

Statistically, the possibility that intervention had no effect on reported robberies cannot be ruled out.¹² In particular, the *treated* areas of Choloma posttreatment look very much like one would expect *given its high pretreatment rate of robbery*. **Figure 3** shows the estimated effect of intervention on areas as a function of pretreatment rate.

¹² See Appendix Table A1, column 2

FIGURE 3

Effect of Intervention on Rate of Reported Robbery



Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

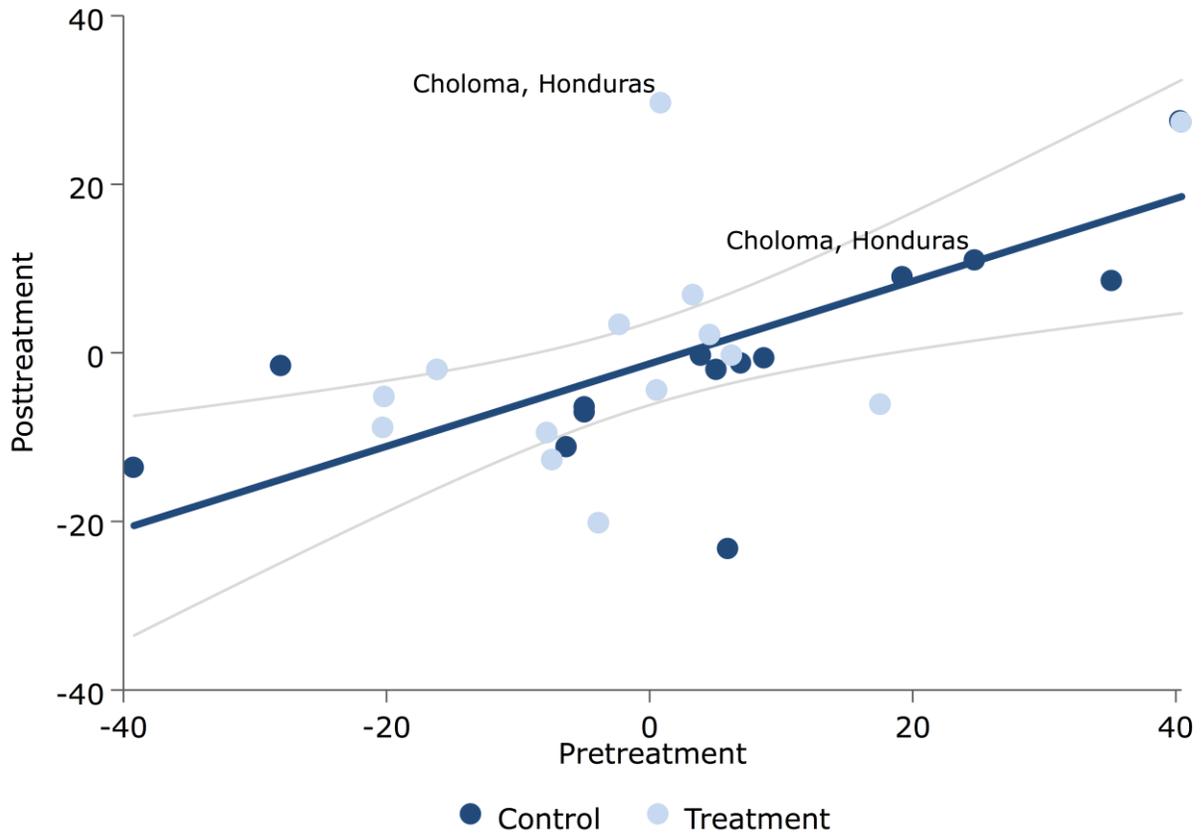
Though this analysis cannot rule out the possibility that there is no effect from intervention, the sample size has been reduced greatly from the thousands surveyed. The test may simply lack the power to detect a small effect.

Nevertheless, this expanded model suggests that for control areas 10 additional percentage points in the pretreatment rate of robbery results in an *additional fall* of 0.5 to 6.8 percentage points over the period of intervention.

As a check, the authors looked not at the rate of reported robbery, but the difference between that rate and the rate for the corresponding country's control areas. **Figure 4** below is identical to Figure 2, but uses this excess rate rather than the raw reported robberies rate.

FIGURE 4

Robbery Reports Adding Treatment Areas Before and After Intervening



Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

Again, it cannot be said that treated areas behave differently than control areas. But the authors find that for every percentage point that a control area's rate exceeds the country pretreatment *control* average, the rate falls 0.2 to 0.8 over the course of intervention. That is, something on the order of half the difference vanishes over time with no intervention. This is reasonable evidence that *unusual* rates of reported robbery are *not* entirely persistent.

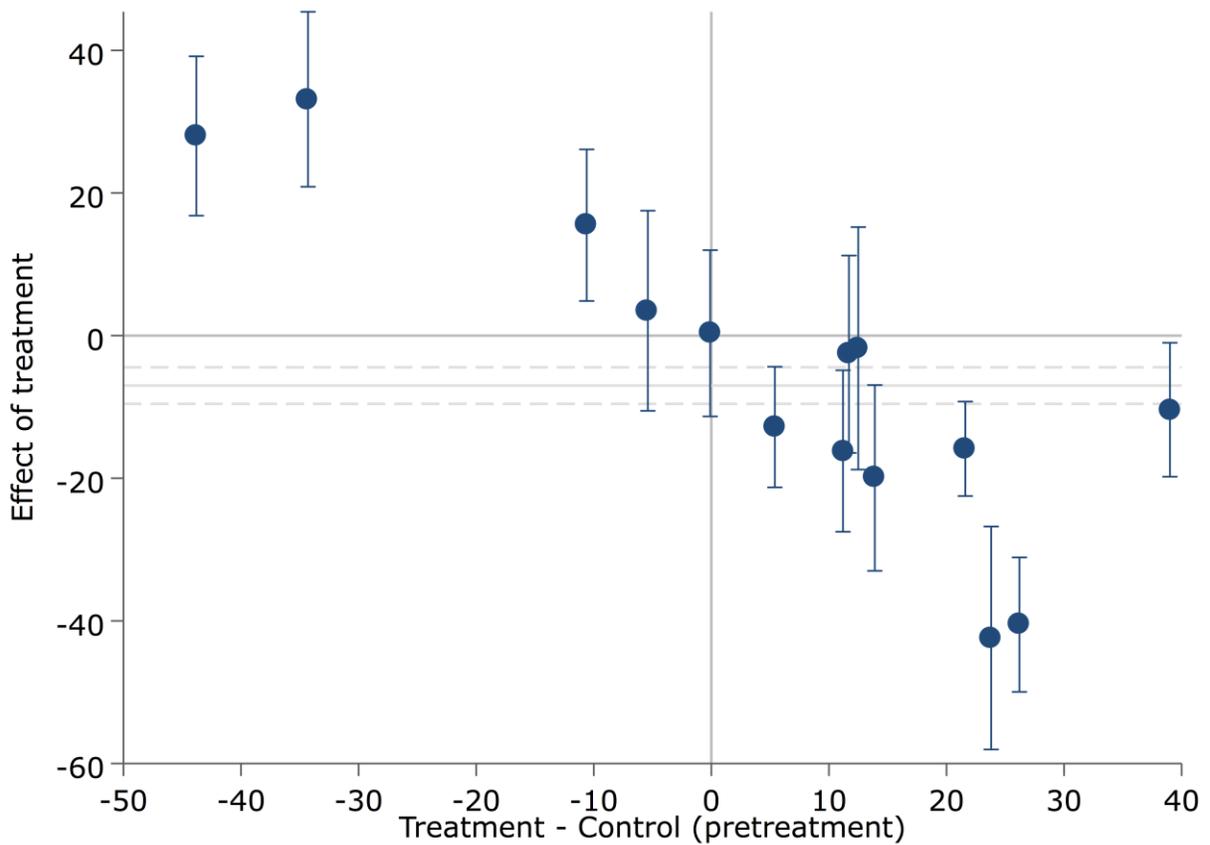
Conclusion

In conclusion, then, if treatment areas happen to have, on average, unusually high rates pretreatment relative to control, one may see an effect of the intervention — even if no such effect exists — unless controlled for expected reversion to the mean.

Now, the LAPOP study’s authors assume that pretreatment differences between treatment and control areas are persistent, and so they do not worry about reversion to the mean. If one assumes otherwise, as the data seems to suggest, then the study’s original models must be expanded to account for those transitory differences.

As a check, the authors repeat the original study using municipality interactions with all the independent variables — much akin to performing separate estimates for each municipality. **Figure 5** shows the estimated effect of treatment on each municipality. The original (constant) treatment effect, found by the LAPOP study, is shown by the gray horizontal line, with the dotted lines indicating a 95 percent confidence interval.

FIGURE 5
Treatment Effects by Municipality



Source: Authors’ calculations based on data supplied by the LAPOP Project at Vanderbilt University.

In Figure 5, the municipalities are placed along the horizontal axis by the difference in average pretreatment survey response on reported robberies between treatment and control areas. That is, treatment areas with low rates of reported robberies relative to their corresponding control areas

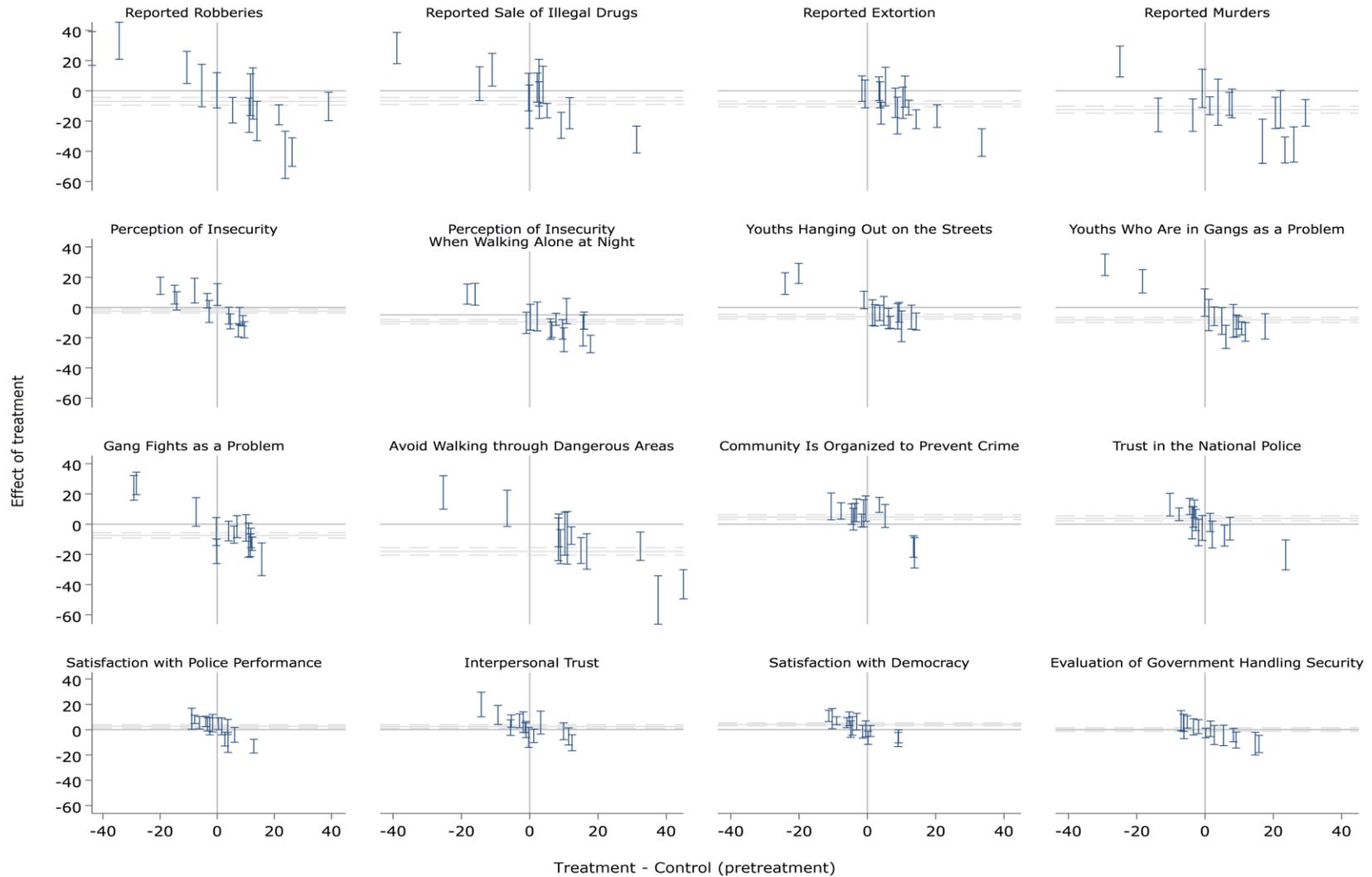
(left) saw robberies *rise* posttreatment when compared to the control. Unsurprisingly, intervention saw the greatest negative effect in Choloma, Honduras, where robbery reports in the control areas rose very rapidly. It seems that successful intervention required high pretreatment robbery rates.

The pattern holds for other indicators as well, since these indicators are related; for example, respondents more likely to report robberies in their neighborhood may be less likely to trust the police. For all 16 indicators there is a negative relationship between the initial difference between treatment and control rates and the supposed effectiveness of the intervention (see **Figure 6**).

It can be seen that the target variables improved more after treatment in areas with relatively poor pretreatment levels, but it is not clear that these target variables improved any more than would be expected without treatment, given the observed pretreatment rates

FIGURE 6

Treatment Effects By Municipality — All Indicators



Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.

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Appendix

Study Models

Take the example of reported robberies — the first indicator of interest. The study results are shown in **Table A1**.

TABLE A1

Respondent-Level Regression Results			
	Study: Without Controls	Study: As Published	Partial Replication with Controls
	(1)	(2)	(3)
Treatment area (β_2)	1.9 (1.1)#	7.8 (2.1)***	7.6 (1.0)***
Posttreatment (β_1)	-5.7 (1.1)***	-5.5 (1.0)***	-5.9 (1.1)***
Treatment (β_3)	-7.2 (1.5)***	-7.9 (1.4)***	-7.3 (1.4)***
Constant (β_0)	42 (0.8)***	31 (6)***	33.3 (6)***
R2	0.01		
Note: treated - control after treatment ($\beta_2+\beta_3$)	-5.3 (1.0)***		0.4 (1.0)
# 10%, * 5%, **1%, ***0.1%			
Source: Authors' calculations based on data supplied by the LAPOP Project at Vanderbilt University.			

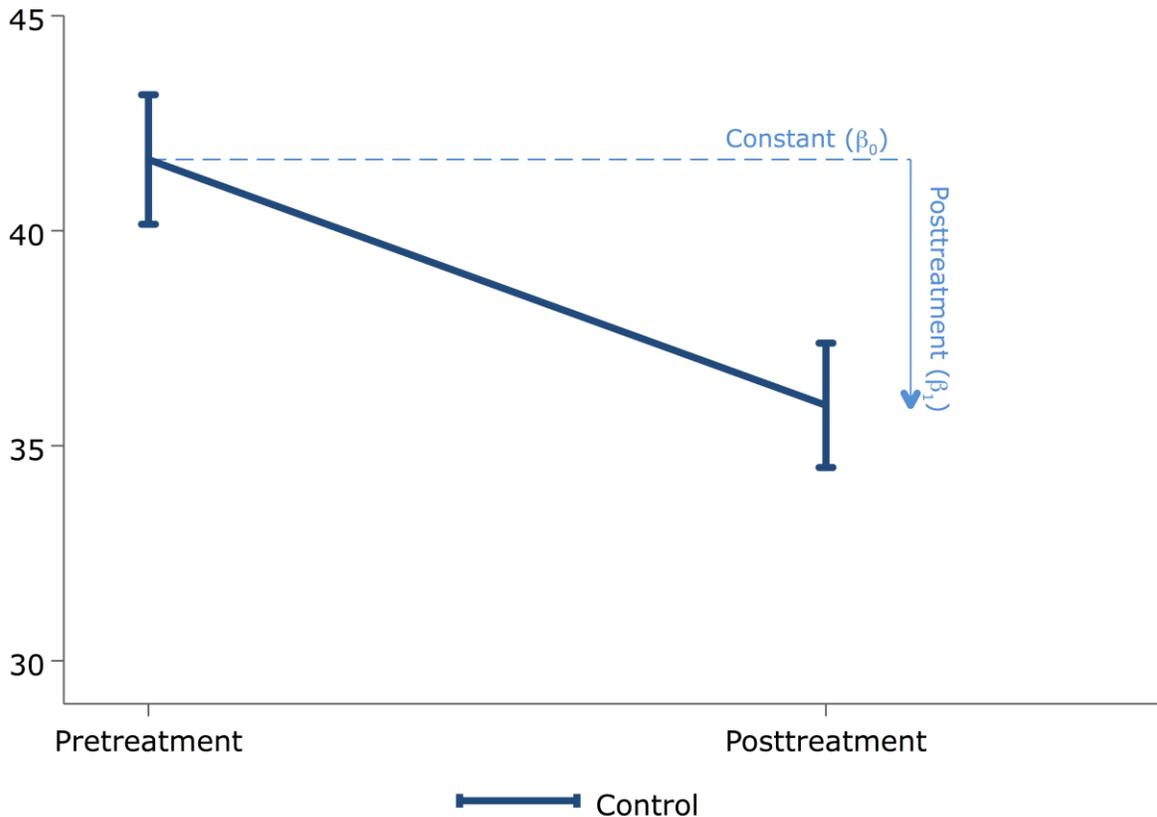
Starting with column 1 — the simplest model may be written:

$$Robbery_i = \beta_0 + \beta_1 PostTreatment_i + \beta_2 TreatmentArea_i + \beta_3 Treatment_i + \varepsilon_i$$

On the left-hand side is a scaled indicator (0/100) variable. A zero says the i^{th} respondent was not aware of a robbery in the neighborhood within the last 12 months; otherwise, Robbery is 100. Now, prior to intervention in the treatment areas, 42 percent of those in *control* areas said they knew of robberies in their neighborhoods in the previous 12 months. Subsequently, the rate fell 5.7 percentage points. The control area initial rate and fall are modeled as β_0 and β_1 , respectively. PostTreatment is a time-based indicator variable equal to 1 after the interventions in treatment areas, so $\beta_0+\beta_1$ would be the estimated posttreatment rate, as seen in **Figure A1**.

FIGURE A1

Estimated Robbery Rates in Control Areas — Before and After Interventions



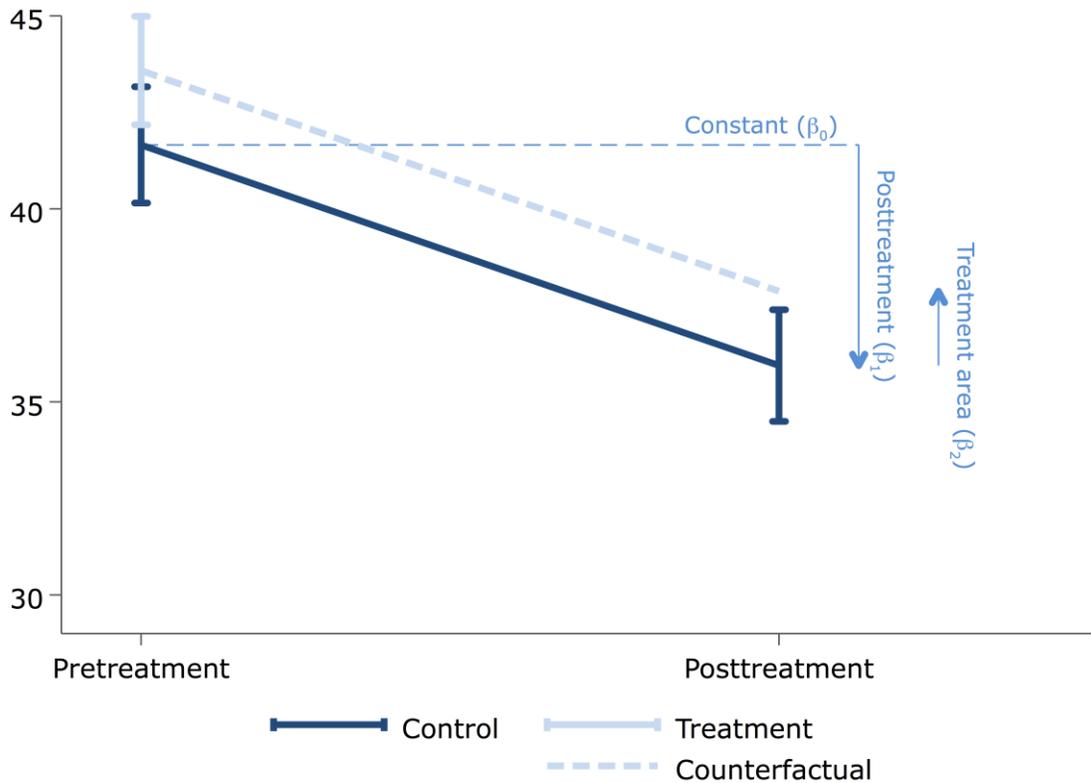
Source: Authors' model

The model estimates are uncertain, so the authors see the likely range for β_0 to be 40 to 43. That is, based on this model, the authors expect 40 to 43 percent of pre-intervention respondents in control areas to report a robbery. Likewise, the authors estimate that the rate fell 3.6 to 7.8 percentage points (based around a 95 percent confidence interval for β_1 , column 1) post-intervention even though no interventions were made in those areas.

Now, prior to intervention, respondents in areas awaiting treatment were marginally more likely to report awareness of at least one robbery in the previous year. *If the interventions had no effect*, then one *might* expect the rate in treatment areas to fall 3.6 to 7.8 percentage points — just as in the control areas. Thus, regardless of the time period, one would expect rates in treatment areas to be 0 to 4 percentage points above that of the control areas. This treatment-area effect is modeled as β_2 where TreatmentArea is another (geographic) indicator set to 1 if the respondent lived in an area subject to intervention. This can be seen in **Figure A2**.

FIGURE A2

Assumed Counterfactual Rates in Treatment Areas If No Effect from Intervention



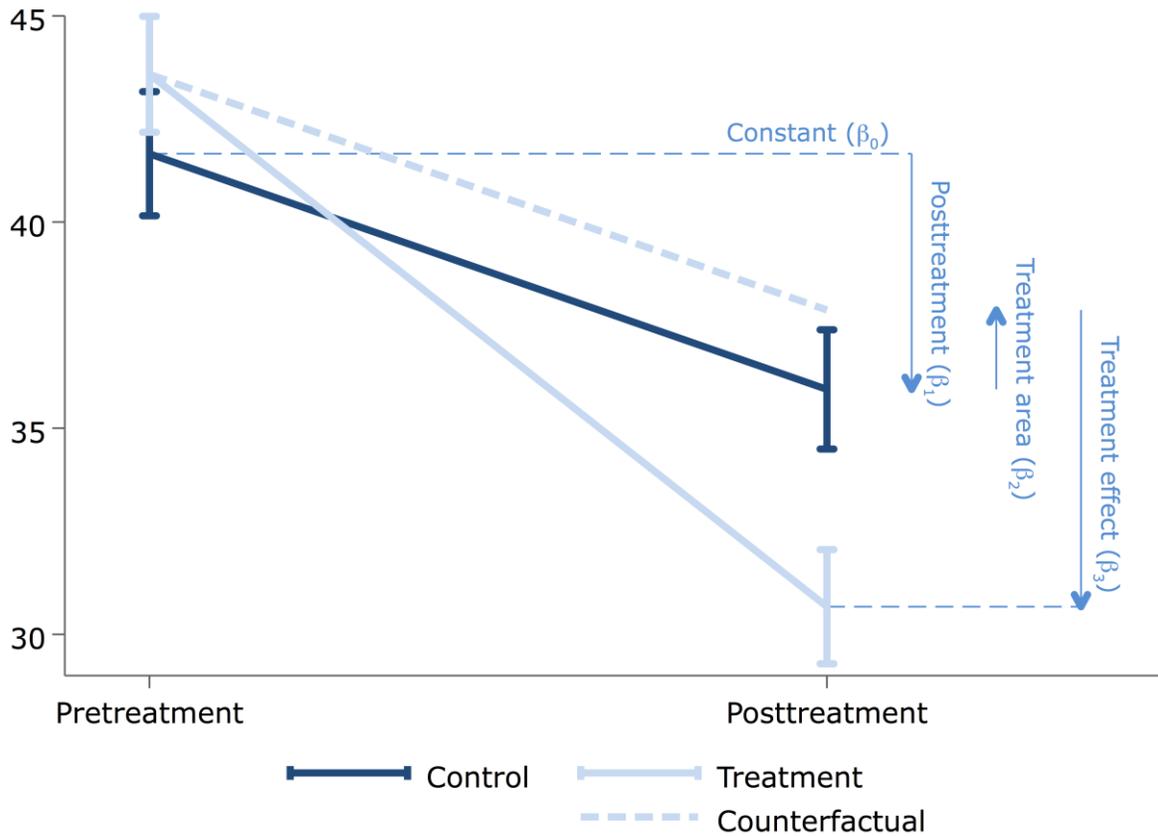
Source: Authors' model

So prior to intervention, the estimated rate in treatment areas would be $\beta_0 + \beta_2$. Post-intervention, the estimated counterfactual rate would be $\beta_0 + \beta_1 + \beta_2$ (the difference being β_1 , just as in the control areas).

It turns out, however, that those treatment areas reported robberies at even lower rates post-intervention; this difference is assumed to be due to intervention. The treatment effect is represented by β_3 where Treatment is a final indicator that is 1 if the respondent lived in an actually treated area. That is, Treatment is 1 if and only if both TreatmentArea and PostTreatment are also 1. Thus, the post-intervention rate in the treatment areas would be $\beta_0 + \beta_1 + \beta_2 + \beta_3$, as seen in **Figure A3**.

FIGURE A3

Complete Study Model (Without Controls)



Source: Authors' model

Including uncertainty in the estimates, the LAPOP study authors infer that the interventions lowered reported robberies by 4 to 10 percentage points. However, this is not the full model used in their study. The full model includes additional control variables:

$$Robbery_i = \beta_0 + \beta_1 PostTreatment_i + \beta_2 TreatmentArea_i + \beta_3 Treatment_i + X_i' \beta_X + \pi_i + \mu_i + \kappa_i + \varepsilon_i$$

Here, X_i represents a vector of individual socioeconomic indicators with coefficient vector β_X ; π_i is a constant random effect corresponding to the respondent's country, μ_i for the municipality, and κ_i for the community. With these additional controls in their model, the LAPOP authors find β_2 to be between 3.6 and 11.9 (95 percent confidence interval).¹³ That is, pre-intervention, those in treated areas reported robbery at a rate some 7.7 percentage points higher than those in control areas.

13 See Table A1, column 2.

Though the data necessary to reproduce these results are not available, column 3 of Table A1 shows a close replication based on the supplied data. All three models suggest similarly sized effects of intervention (β_3).

Added Models

Moving beyond the models presented in the LAPOP study, the authors shift from examining the survey results at the respondent level to modeling the area-level average posttreatment responses *using observed pretreatment averages*.¹⁴ The baseline model (see **Table A2**, column 1, “Post-Treatment Rate, Control Areas Only”) is very simple. Using control areas only,

$$Rate_{i,1} = \beta_0 + \beta_1 Rate_{i,0} + \varepsilon_i$$

where $Rate_{i,0}$ is the pretreatment rate for area i , and $Rate_{i,1}$ is the corresponding posttreatment rate.

Column 2 (“Post-Treatment Rate, All Areas”) of Table A2 expands on this by including treatment areas. This model adds a complete set of interactions for treatment area, though a joint F-test shows that these additional variables add nothing important — the treatment areas are effectively identical to control areas once pretreatment rates are accounted for.

$$Rate_{i,0} = \beta_0 + \beta_1 Rate_{i,0} + \beta_2 TreatmentArea_i + \beta_3 TreatmentArea_i \times Rate_{i,0} + \varepsilon_i$$

¹⁴ “Area” is defined here as (alternatively) the aggregate neighborhoods — control or treatment — within a single municipality. That is, there are exactly *two* observations per municipality.

TABLE A2

Area-Level Regression Results

	Posttreatment Rate		Posttreatment Rate – Country’s Control Average	
	<i>Control Areas Only</i> (1)	<i>All Areas</i> (2)	<i>Control Areas Only</i> (3)	<i>All Areas</i> (4)
Pretreatment rate (β_1)	0.65 (0.18)***	0.66 (0.16)***	0.49 (0.19)*	0.48 (0.16)**
Pretreatment rate \wedge (β_3)		0.04 (0.24)		-0.10 (0.19)
constant \wedge (β_2)		-4 (11)		-0.5 (3.4)
constant (β_0)	6.9 (7.7)	5.3 (6.9)	-1.3 (2.9)	-1.3 (2.4)
Note: Joint F-stat [p] testing all zero interactions ($\beta_2=\beta_3=0$)		0.16 [0.86]		0.14 [0.87]
Note: Mean reversion ($\beta_1 - 1.0$)	-0.35 (0.18)#	-0.34 (0.16)*	-0.51 (0.19)*	-0.51 (0.16)*

Source and Notes: Authors’ model
 Regressions are robust to outliers
 \wedge Interacted with indicator for treatment area
 # 10%, * 5%, **1%, ***0.1%

In column 3 (“Posttreatment Rate – Country’s Control Average, Control Areas Only”), the authors use the same model as column 1, but subtract the country-wide rate pooling over respondents in all its *control* areas. If the country-*j* average $P_{j,0}$ is pretreatment and $P_{j,1}$ is posttreatment, then for control areas only:

$$Rate_{i,1} - P_{j,1} = \beta_0 + \beta_1(Rate_{i,0} - P_{j,0}) + \varepsilon_i$$

Finally, column 4 (“Posttreatment Rate – Country’s Control Average, All Areas”) is similarly expanded to include treatment areas of each municipality.

$$Rate_{i,1} - P_{j,1} = \beta_0 + \beta_1(Rate_{i,0} - P_{j,0}) + \beta_2TreatmentArea_i + \beta_3TreatmentArea_i \times (Rate_{i,0} - P_{j,0}) + \varepsilon_i$$

Note that $P_{j,t}$ are still defined exclusively by the aggregate control areas of the country; for a treatment area, $Rate_{i,t}-P_{j,t}$ is the municipality’s treatment area average for the period, less the country’s control average for the period.