Intelligent Policing and Homicide Prevention: Using the Synthetic Control Method to Estimate the Effect of Policy Implementation[*]

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Abstract

Although Brazil remains severely affected by civil violence, the state of São Paulo has made significant inroads in fighting criminality. In the last decade, São Paulo has witnessed a 70% decline in homicide rates, a result that policy-makers attribute to a series of crime-reducing measures implemented by the state government. While recent academic studies seem to confirm this downward trend, no estimation of the impact of state policies on homicide rates currently exists. In this article, we fill this gap by employing the Synthetic Control Method to compare these measures against an artificial São Paulo. The results indicate a large drop in homicide rates in actual São Paulo when contrasted with our synthetic counterfactual, with about 20,000 lives saved during the period. The theoretical usefulness of the Synthetic Control Method for public policy analysis and the practical implications of the security measures taken by the São Paulo state government are also discussed.

KEYWORDS: Brazil, homicides, urban violence, crime prevention, synthetic control

1 Introduction

Brazil has long been ravaged by an undeclared civil war. According to the Citizen Council on Public Security and Criminal Justice, a Mexican think-tank, no less than 19 of the 50 most violent cities in the world are located in Brazil (Consejo Ciudadano para la Securidad Pública y Justicia Penal, 2014).[1] The 2014 Violence Map survey shows that 56,337 people were murdered in Brazil in 2012 alone (Waiselfisz, 2014), the highest incidence of intentional homicides on the planet (United Nations Office on Drugs and Crime, 2013). Paradoxically, the sharp rise in lethal violence has occurred during Brazil's longest period of political openness (Ahnen, 2003; Pinheiro, 2000, 2001). Over the past three decades, murder rates have increased by 148%, jumping from 11.7 homicides per 100,000 people in 1980 to roughly 29 per 100,000 in 2012 (Waiselfisz, 2014).[2] It seems democracy has yet to bring peace to the Latin American giant.

São Paulo traditionally occupied a key position in Brazil's violence statistics. It is Brazil's richest (IBGE, 2012) and most-densely populated state (IBGE, 2014), and in the 1990s its homicide rate (31.6 per 100,000) was roughly 50% higher than the national average (Barata and Ribeiro, 2000). Some areas of the namesake capital city had even worse numbers. Between 1996 and 1999, the ramshackle districts of Jardim Ângela and Jardim São Luiz had 116 and 103 violent deaths per 100,000 residents (Cardia et al., 2003, 8), which placed them amongst the deadliest neighborhoods on the globe (World Health Organization, 2015).

Nevertheless, São Paulo has experienced a drastic reduction in homicides during the past years (Camargo, 2007). The decline is so remarkable that some authors have called it "the great homicide drop" (Goertzel and Kahn, 2009). As an example, in the city of São Paulo murders declined from 5,979 to 1,311 from 2000 to 2007, a 78% decrease.[3] Even more impressive figures could be seen in the capital's poorest areas. In absolute terms, homicides in Capão Redondo declined from 203 in 2002 to

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[1]The study disregards war zones and cities with unavailable data.

[2]Cerqueira (2013) argues that the actual rates may be different from the official statistics. He states that many homicides from 1996 to 2010 were (intentionally or not) misclassified as "death by undetermined causes." After performing data correction procedures, the author estimates that the number of homicides in Brazil during that period should be 18.3% higher than the reported figures. Recent criticism about the quality of São Paulo homicide data can also be found at http://www.brasilpost.com.br/2016/01/29/bolsonaro-homicidios-alckmin_n_9102858.html. Access: 30 January, 2016.

[3]The homicide statistics cited in that paragraph come from the Centre for the Study of Violence, a research group of the University of São Paulo. Their dataset can be found at the following electronic address: http://nevusp.org/downloads/bancodedados/homicidios/distritossp/num-homicidios-distritos-2000-2007.htm. Access: 25 March, 2015.

23 in 2007; in Itaquera, from 140 in 2001 to 20 in 2007; in Cidade Tiradentes, from 195 in 2000 to 24 in 2007; and in Jardim Ângela there were 53 homicides in 2007, down from 277 in 2001. Significantly, the city of São Paulo became the least violent capital in the whole country (Waiselfisz, 2011).

Interestingly, this downward trend is *not* linked to a country-wide drop in murder rates. From 2001 to 2005, apart from a slight decrease in the number of homicides in the state of Rio de Janeiro, Brazil did not experience any significant decline in violent deaths (Goertzel and Kahn, 2009). Recent evidence suggests that homicide rates have actually *increased* in other parts of the federation, mainly in the poor North-East region (de Sousa et al., 2014). Hence, the homicide reduction in São Paulo should be attributed to local factors.
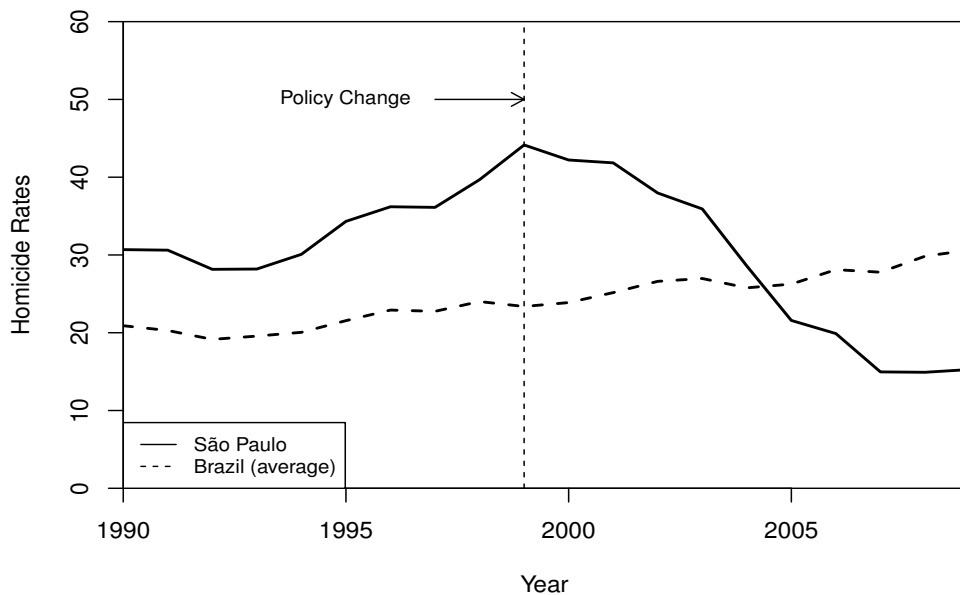

Figure 1: *Homicide Rates per 100,000 Population – São Paulo and Brazil (Excluding São Paulo)*

A myriad of explanations have been proposed for this phenomenon. While some authors have stressed the importance of socio-economic factors such as the changing age structure (de Mello and Schneider, 2010) or spatial segregation patterns in São Paulo (Hughes, 2004), others have argued that the relationship between structural variables and violent deaths are actually not conclusive (de Mendonça et al., 2003). In this article, we espouse the view that the lower levels of violence

in São Paulo are the outcome of deliberate public policies targeting crime. The Brazilian Social Democracy Party (*Partido da Social Democracia Brasileira – PSDB*), which has ruled São Paulo since 1995, has repeatedly asserted its commitment to reducing urban crime throughout the state (Bueno, 2014). In 1998, former governor Mário Covas—then running for re-election—set the ambitious goal of "slashing criminality rates in half" during his second term in office (Santos, 2008). This commitment was then followed by his vice-governor and successor, Geraldo Alckmin, who has also taken a notoriously tough stance on crime (Feltran, 2012).

From 1999 onwards, the state government created or expanded several policies that arguably contributed to the decrease in criminality in São Paulo. First, the government implemented gun control policies, which have apparently had a large impact on the incidence of violence (Goertzel and Kahn, 2009; Nadanovsky, 2009). Moreover, incarceration rates have skyrocketed in the past decade (Salla, 2007). São Paulo currently holds around 200,000 convicts (35% of Brazil's inmate population) and adds another 15,000 inmates to the official statistics every year (Brasil de Fato, 2013). Furthermore, prisoners have also been subject to harsher legal punishments. The state government has been making large use of the *Regime Disciplinar Diferenciado* (Special Disciplinary Regime), which dictates that convicts may stay up to 360 days in solitary confinement for disobeying the law (Carvalho and Freire, 2005).

Methods of crime prevention have also received attention by the authorities. Recently, the state has invested in police intelligence, gathered geocoded crime statistics, expanded community policing programmes and improved intergovernmental communication between different police branches (Goertzel and Kahn, 2009). Combined with the repressive policies mentioned above, one may reasonably argue that both the certainty and the severity of punishment (Becker, 1974) have increased in São Paulo.

By the late 2000s, São Paulo's violence statistics were much lower than expected. In ten years, homicide rates were cut by about 70% (Feltran, 2012). While in 1998 it was the fifth most violent state in Brazil, in 2008 São Paulo was the third from last (25th out of 27) (Waiselfisz, 2011). It is difficult to know, however, which of the policies have contributed more to this large homicide reduction. Not only we do not have disaggregated data to test preliminary hypotheses, but there are also probably large interaction effects among different public security measures. Therefore, it is not

possible for us to disentangle micro-level causes from macro effects. Still, we believe that there is a causal relationship between these public policies and crime levels; such a significant drop is unlikely to be caused by chance alone.

Nonetheless, one question remains. If the specific effect of each measure is impossible to gauge, could one assess at least the aggregated impact of those anti-crime policies? Thus far, the literature offers no definitive answer to this problem. Although many scholars acknowledge the decrease in lethal violence in São Paulo, few studies go beyond simple regression models and try to estimate policy effects. We understand that such an exercise is not trivial. On the one hand, São Paulo can hardly be compared with other Brazilian states given its social, demographic and economic position. On the other hand, commonly-employed research techniques offer little guidance as to estimate policy effects when no counterfactual is readily available.

In this article we employ the Synthetic Control Method (SCM) to tackle these issues. The method consists of creating an artificial counterfactual to estimate the impact of a given intervention over a unit of interest (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2011). Here, we shall employ this method to calculate the impact of post-1999 public policies on São Paulo homicide rates. SCM has gained widespread acceptance in many fields of science, having been successfully applied in political science (Abadie et al., 2014; Montalvo, 2011), economics (Billmeier and Nannicini, 2013; Coffman and Noy, 2012; Jinjarak et al., 2013), education (Hinrichs, 2012) and public health (Heim and Lurie, 2014). However, it has rarely, if ever, been applied to evaluate violence-reduction strategies. SCM is particularly useful to our topic because it allows us to estimate policy effects when the number of treated units is 1 and there is no readily available counterfactual case. Therefore, our study brings an innovative way to analyse one of Brazil's most pressing problems and may foster a renewed debate on anti-crime programs and public policy evaluation.

The article proceeds as follows. In the next section, we present the theoretical underpinnings of the SCM and demonstrate how this method is useful to our purposes. In the third section, we describe the variables used in this study and present our findings. Section four concludes and discusses possible extensions of this work.

2 Methods

The synthetic control approach provides an adequate solution for two enduring problems in the social sciences: the arbitrary selection of comparative cases and the poor estimation of causal effects when few pre-treatment observations are available (Abadie and Gardeazabal, 2003; Abadie et al., 2010). With respect to the first issue, scholars often resort to ambiguous criteria in their choice of control units, which ends up casting doubts over the validity of their selected counterfactual (Abadie et al., 2011). The synthetic method provides a reliable comparative case by weighting comparable examples and pooling the candidates into a single control unit (Abadie et al., 2010). As this is a purely data-driven process, SCM does not adopt arbitrary procedures in order to select a counterfactual. Regarding the second issue, the accurate estimation of coefficients from a small number of cases, SCM employs a consistent statistical solution to problems of incorrect data extrapolation and model dependence (Ho et al., 2007). Since the synthetic case is constructed with a weighted average of theoretically suitable controls and the weights sums to 1, there is no risk of unrealistic predictions. Additionally, the weights make explicit the contribution of each separate case to the synthetic control, thus increasing the transparency and reliability of the counterfactual (Abadie et al., 2014).

SCM also has an intuitive interpretation. Although numeric summaries and model statistics can be obtained from the model, one can easily grasp the treatment effect (or lack thereof) by simply comparing two time trends. A straightforward time series graph is usually enough to assess if the treated unit and the synthetic control case are diverging or not.

Furthermore, placebo tests can be run to test the robustness of the findings. Researchers can either include "in-time placebos", dates under which the treatment *did not* occur, or "in-space placebos", which is to add different members of the donor pools into the models (Abadie et al., 2014).

Formally, the method works as follows.[4] Let $j = 1, \ldots, J + 1$ be a series of units in periods $t = 1, \ldots, T$. In our case, our units are the 27 Brazilian federal states. Assuming that the first unit, São Paulo, has been exposed to the treatment, we have J control units to be included in the case studies' donor pool, or 26 remaining states. We define treatment as the series of post-1999 government anti-crime policies implemented in the São Paulo.

Let Y_{it}^N be the homicide rate that would be observed for unit i, São Paulo, at time t with no

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[4]The next paragraphs summarise the approach described in Abadie et al. (2010).

treatment. Conversely, let Y_{it}^I be the observable outcome for unit i at time t had it been subjected to the treatment in periods $T_0 + 1$ to T. An important assumption is that the treatment has no effect on unit i before the date of intervention, therefore $Y_{it}^I = Y_{it}^N \ \forall t < T_0$. The observed outcome is defined by $Y_{it}^I = Y_{it}^N + \alpha_{it} D_{it}$, where α_{it} is the effect of crime-reducing policies on homicide rates $(Y_{it}^I - Y_{it}^N)$ and D_{it} is a binary variable that takes the value of 1 if we refer to post-intervention period (after 1999) and 0 otherwise. The goal of this paper is to estimate α_{it} for the state of São Paulo for all $t \geq T_0$. However, we can never observe Y_{it}^N for unit i in $t \geq T_0$, only Y_{it}^I (Holland, 1986). But although there is no way to accurately estimate Y_{it}, we can approximate it by using a weighted average of the remaining units in the donor pool such that $Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it}$. In this model, δ_t is an unobserved time-dependent factor common to all cases, Z_i is a $(1 \times r)$ vector of observed covariates not affected by the policy, θ_t is a $(r \times 1)$ vector of unknown time-specific parameters, λ_t is a $(1 \times F)$ vector of unknown common factors to all states, μ_i is a state-specific unobservable variable and ϵ_{it} represents unobserved transitory shocks with mean 0 for all units. Basically, what SCM tries to do is to match Z_i and the pre-treatment Y_{it} of the treated unit so that μ_i is matched as a result.

To reaffirm, synthetic São Paulo is the weighted average of the other 26 remaining Brazilian states. Therefore, it is a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{J+1})'$ with $w_j \geq 0$ for $j = 2, \ldots, J+1$ and $w_2 + \cdots + w_{J+1} = 1$. Each of the elements included in W represents a specific weighted average of control states, that is, a potential synthetic control for São Paulo. The idea is to select a case that resembles the treated unit as closely as possible. Let X_1 be a $(k \times 1)$ vector of pre-1999 predictor variables for São Paulo and let X_0 be a $(k \times J)$ matrix containing the predictor variables for the potential control states. Let $\bar{Y}_i^{K_1}, \ldots, \bar{Y}_i^{K_M}$ be M linear functions of pre-treatment outcomes $(M \geq F)$. One can choose w^* such that:

$$\sum_{j=2}^{J+1} w_j^* Z_j = Z_1, \ \sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_1} = \bar{Y}_1^{K_1}, \ldots, \sum_{j=2}^{J+1} w_j^* \bar{Y}_j^{K_M} = \bar{Y}_1^{K_M}$$

Consequently, as noted by Abadie and his collaborators (2010), if T_0 is sufficiently large when compared to the scale of ϵ_{it}, an approximately unbiased estimator for α_{1t}, the effect of public security policies in São Paulo, can be described by:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}$$

for all $t \in \{T_0 + 1, \ldots, T\}$, that is, after the intervention period (1999–2009). In practice, W^* is chosen non-parametrically as to minimise $||X_1 - X_0 W||$, subject to the weight constrains. We consider $||X_1 - X_0 W|| v = \sqrt{(X_1 - X_0 W)'V(X_1 - X_0 W)}$, where V is a $(k \times k)$ symmetric and semi-definite positive matrix with the relative importance of each assigned homicide rate predictor. From various possible ways to choose V, in this paper we follow the recommendation of Abadie et al. (2010) and choose V^* as the value of V that minimises the mean squared prediction error (MSPE) for homicide rates in the entire pre-treatment period (1990-1998).

3   Data

We build panel data for the variables *Homicide Rate*, *State GDP per Capita*, *State GDP Growth*, *Years of Schooling*, *Gini Index*, *Natural Logarithm of Population* and *Population Living in Extreme Poverty*. These variables are very common in the specialised literature[5] and represent important social and economic factors we wish to control for. The unit of analysis is state-year. We have data from all of the 26 states plus the capital city (*Distrito Federal*), ranging from 1990 to 2009. The data for years prior to 1990 are scarce and for years after 2009 have not been published in a comparable format. Our source for all variables was the *Instituto de Pesquisa Econômica e Aplicada* (IPEA), a government-led research group.[6] Our dependent variable measures the number of homicides per 100,000 inhabitants, which is the most commonly used unit of analysis for lethal violence. *State GDP per Capita* is adjusted in 2010 Brazilian Reals (at the time 1 Brazilian Real bought roughly 0.5 U.S. dollars). *State GDP Growth* is measured in constant 2010 Brazilian Reals and varies by percentage points. *Years of Schooling* describes the average number of years of formal instruction at educational facilities (males and females, 25 years old or more.) *Gini Index* is a measure of inequality, ranging from 0 to 1 where 0 is the most equal and 1 the most unequal state. *Natural Logarithm of Population* represents yearly projections of the state population. Since Brazil only runs a census every 10 years,

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[5]For overviews of cross-national studies of homicide, see LaFree (1999), Nivette (2011) and Trent and Pridemore (2012).

[6]The data are publicly available at http://www.ipeadata.gov.br/. The original data files have also been added to our GitHub repository for reproducibility purposes.

these projections represent the most accurate data available. We have taken the natural logarithm of this variable to account for size effects. Finally, *Population Living in Extreme Poverty* describes the percentage of the state population which do not meet the minimum intake of 2,000 calories per day. This is the only variable which we created specifically for this study. It was coded by simply taking the number of individuals classified as extremely poor by the IPEA and dividing by the state total population.[7]

4   Analysis

We construct our synthetic control case (*Synthetic São Paulo*) by imputing information from all of the Brazilian states plus the Federal District. The synthetic control method outputs a set of weights for states and variables such that the treatment state is approximated optimally by these weighted components. This method not only provides us with a quantitative way of selecting comparison cases but also gives us a much better baseline to compare with the treatment unit. Synthetic São Paulo is constructed using six states, *i.e.*, only six out of 27 possible cases receive non-zero weights. Table 1 shows that the states that best synthesize São Paulo are, respectively, Santa Catarina (0.274), Distrito Federal (Brasília) (0.210), Espírito Santo (0.209), Rio de Janeiro (0.169), Roraima (0.137) and Pernambuco, which only accounts for 0.01 of the weights. In this regard the state selection does not appear as a complete surprise to us. Apart from Roraima, the other members of the federation are richer, more densely populated and better schooled than the country average, thus being indeed similar to São Paulo.

Table 1: *Synthetic Weights for São Paulo*

State	Synthetic Control Weights	Predictor	Weights
Santa Catarina	0.274	*Years of Schooling*	0.469
Distrito Federal	0.210	*State GDP per Capita*	0.275
Espírito Santo	0.209	*Homicide Rate*	0.241
Rio de Janeiro	0.169	*Population Living in Extreme Poverty*	0.009
Roraima	0.137	*Gini Index*	0.005
Pernambuco	0.001	*Ln Population*	0.001

Among the independent variables, only three out of six receive substantial weights. Given the

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[7] *Years of Schooling* and *Gini Index* had a small number of missing observations (about 15 percent) and those cases were imputed with linear interpolation. Both original and imputed variables are available in our dataset.

data we could obtain, the predictors that receive more weight are Years of Schooling (0.469), State GDP per Capita (0.275) and past Homicide Rate (0.241). The three remaining variables are much less relevant to the model. They are, respectively, the Population Living in Extreme Poverty (0.009), Gini Index (0.005) and Natural Logarithm of the Population (0.001). Table 2 compares characteristics of São Paulo and its synthetic control prior to policy implementation. We can see that Synthetic São Paulo has coefficients very similar to those of the treatment unit. Moreover, our synthetic control outperforms the sample means in all of the three relevant predictors. The worst measure is State GDP Growth, whose mean is about 2.6 whereas the figure for São Paulo is roughly 1.3 during that period. However, this outcome does not affect our results because the variables that received zero weight were discarded from our models.

Table 2: *Homicide Rate Predictor Means Before Policy Implementation*

Predictor	São Paulo	Synthetic São Paulo	Sample Mean
Years of Schooling	6.089	6.110	4.963
State GDP Per Capita	23.285	23.079	11.830
Homicide Rate	32.672	32.479	21.843
Population Living in Extreme Poverty	0.054	0.082	0.185
Gini Index	0.536	0.561	0.578
Ln Population	17.335	14.838	14.867
State GDP Growth	1.330	2.585	3.528

Our results show that the Synthetic Control Method has successfully created a valid counterfactual to our case of interest. Figure 2 depicts the evolution of the dependent variable for the treatment and synthetic control cases, and Figure 3 shows the gap in the homicide rate between the treated and the control unit. We can see that São Paulo and Synthetic São Paulo have very close homicide rates series for the period ranging from 1990 until 1998. From 1999 onwards we have the trajectories departing sharply from each other. The increase in homicide rates shown in the graph is consistent with previous statistical evidence. It indeed confirms that São Paulo had higher than expected levels of lethal violence, which we noted in the first part of this text.
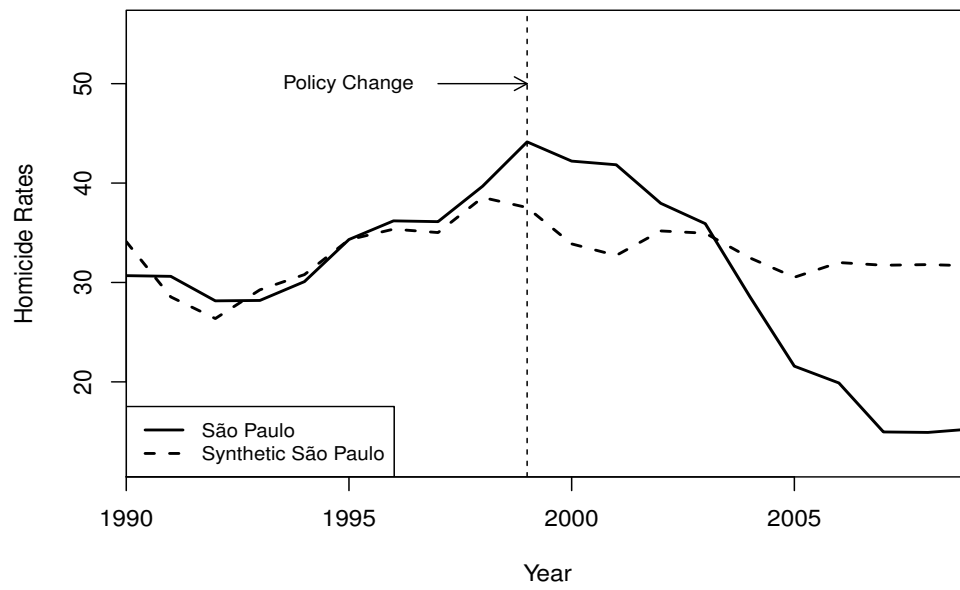
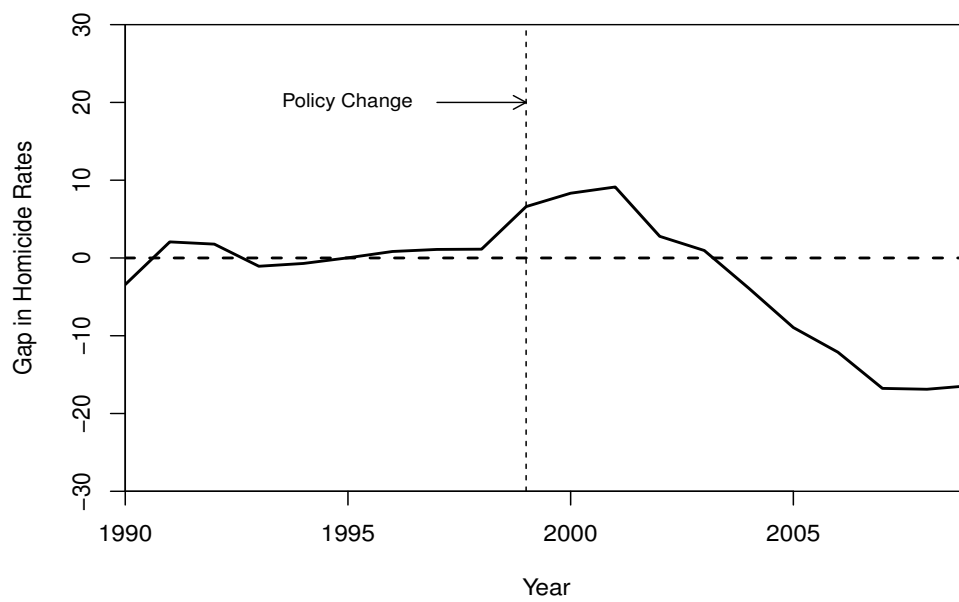Figure 2: *Trends in Homicide Rates: São Paulo versus Synthetic São Paulo*

Figure 3: *Homicide Rates Gap between São Paulo and Synthetic São Paulo*

11

The graphs confirm our initial guesses. Despite the high levels of violence in 1999—when the new crime-reducing programme was implemented—the number of homicides consistently declined until 2009. The trend is indeed monotonic and there are no peaks in homicide rates after the policies have been put into practice. We see that as an evidence in favour of the public policies.

With respect to the size of the effect, in 1998 the homicide rate in São Paulo was around 40 deaths per 100,000 inhabitants. In 2009—the last year for which data are available—the rate dropped to 15 whereas Synthetic São Paulo observed above 30 deaths per 100,000. That means a gap of −20 deaths for every 100,000 people in São Paulo in 2009, as can be seen in Figure 3. We estimate that the new policies implemented in São Paulo saved roughly 20,300 lives in the period from 1999 to 2009.[8]
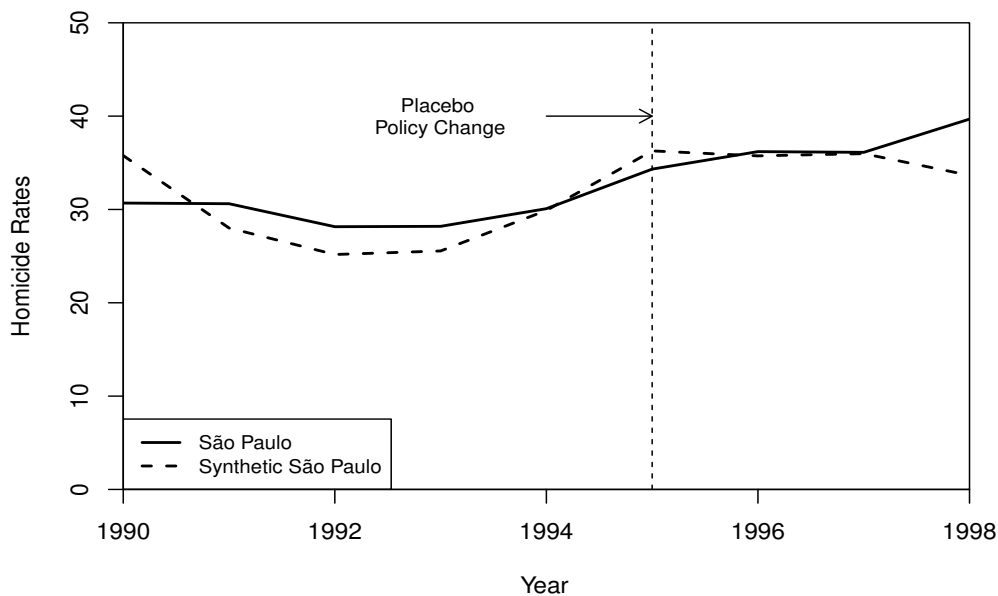

Figure 4: *Placebo Policy Implementation 1994—Trends in Homicide Rates: São Paulo versus Synthetic São Paulo*

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[8]Our estimate of lives saved by the policies implemented in São Paulo is done as follows. We consider the years after policy implementation (1999-2009), then we sum the number of homicides in São Paulo in that period. This gives us 124,077 homicides between 1999 and 2009. We do the same procedure for the Synthetic São Paulo; we sum the number of homicides in each state that makes the synthetic control in the period, while adjusting the contribution of each of these states by their respective weights in the synthesis. The number of homicides in the Synthetic São Paulo between 1999 and 2009 is 144,408. Finally, we subtract the number of homicides in the control by the number of homicides in the treatment, which results in our estimate of lives saved, 20,331.

To further analyse our findings, we run four robustness tests. We first create an "in-time placebo" synthetic control to test whether the counterfactual provides a good prediction even if the intervention did not occur (Abadie et al., 2014). If that were to be the case, the validity of our results could be put into question. The result of this placebo test can be seen in Figure 4. When we run the optimisation algorithm with 1994 as the year when there was a supposed policy change, the result shows that there is only a minor gap between both lines. In other words, the method does not indicate a definite departure of trends between treatment and control cases.

We also have a leave-one-out robustness test. In this test we drop the states composing the synthetic control one at a time. The results of this analysis can be found in Figure 5. We see that the synthetic control (dashed line) is a reasonable amalgam of cases since it is bounded by the other estimates. Also, because the relative positions of treatment and controls are stable across controls, we observe that no single state is driving the results.
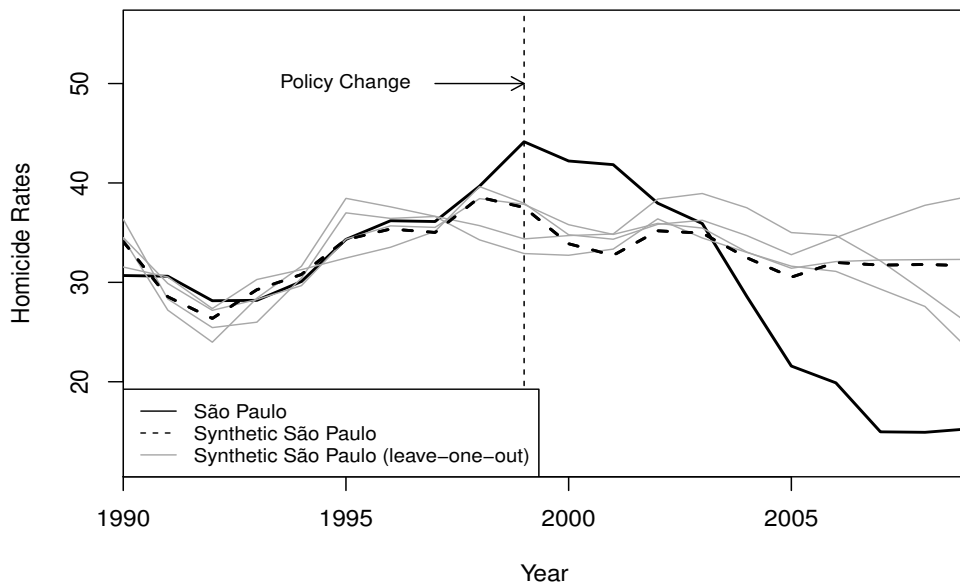

Figure 5: *Leave-One-Out Distribution of the Synthetic Control for São Paulo*

Figure 6 shows the difference in homicide rates between the treated units and their synthetic controls. Here we include not only São Paulo and its simulated counterfactual, but placebo synthetic

controls for the remaining 26 Brazilian states. We see that in São Paulo the homicide rate gap increases consistently during the treatment period, whereas the lines for the other states are moving randomly. Several lines fail to show any substantial difference between the state trend and that of its synthetic counterfactual case. This indicates the results for São Paulo are unlikely to be model dependent or a mere statistical fluke.
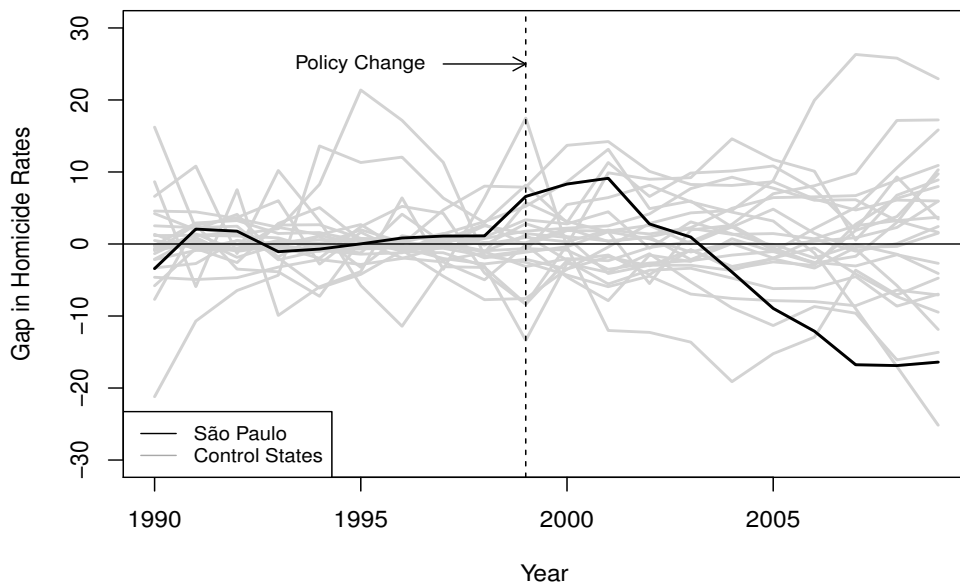

Figure 6: *Permutation Test: Homicide Rate Gaps in São Paulo and 26 Control States*

Lastly, we add an even more strict robustness test. We focus on those placebo synthetic controls which have MSPE not higher than twice the MSPE of synthetic São Paulo (Abadie et al., 2010). This means that only states that have produced very reliable counterfactuals are included in the analysis. Many of them, such as the neighbouring states of Minas Gerais or Paraná, have actually *better* fit than our treatment case. As we see in figure 7, the gap for São Paulo remains the largest amongst the 12 states in the sample. The graph provides strong support to our original claims: the negative effect on homicide rates is indeed stronger in São Paulo than in other states with similar, or better, synthetic controls.
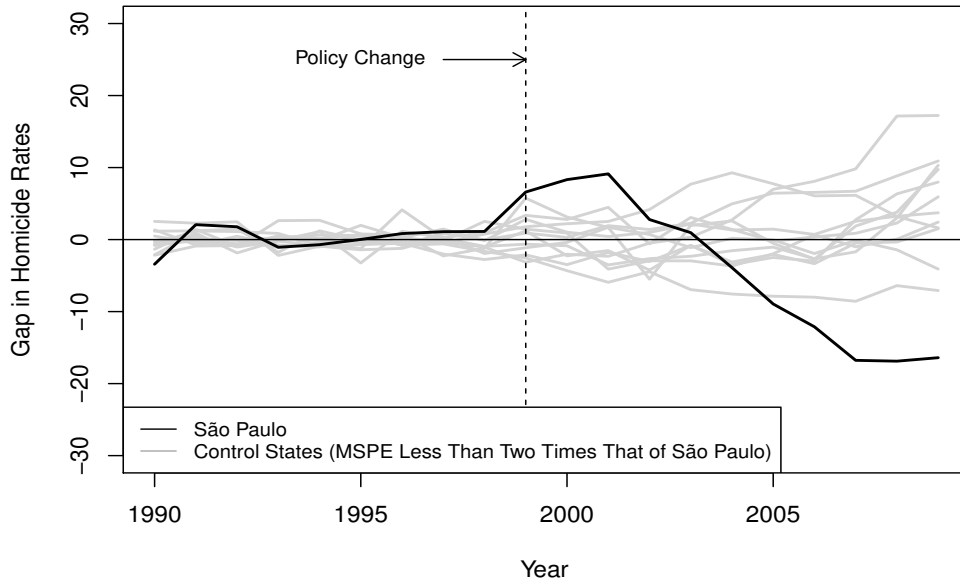
Figure 7: *Permutation Test: Homicide Rate Gaps in São Paulo and 12 Control States (MSPE Less Than Two Times That of São Paulo)*

5   Concluding Discussion

As we have demonstrated, when compared to a synthetic control case, homicide rates were drastically reduced in São Paulo. Although it is not possible for us to estimate the treatment effect of each specific policy implemented during the 1990s and 2000s, we suggest that their aggregate impact was surely not negligible. In this regard, the state of São Paulo offers a clear example that it is feasible to fight crime with targeted policies. We see this as an encouraging result, as it suggests that governments can make progress in reducing crime with resources they already have at hand and need not rely exclusively upon structural conditions that are largely beyond their control such as unemployment, per capita income and inequality. Robustness tests provide further evidence for our findings.

Whereas the overall effects of the new security policies in São Paulo have been positive, it has also created adverse outcomes. Paradoxically, the recent increase in the prison population in the state of

15

São Paulo—a by-product of harsher criminal policies—has created what today constitutes the most serious threat to public security in the state: the *Primeiro Comando da Capital* ("First Command of the Capital", PCC), Brazil's most powerful prison gang (Dias, 2009; Souza, 2007). The PCC staged two high-profile attacks against police forces (2001 and 2006), currently dominates about 90% of the prisons in São Paulo, has established itself in 22 of the 27 Brazilian states, makes profits of about 50 million dollars per year and has allegedly elected their own representatives in Brazil's last elections (Biondi, 2010). Therefore, the state government now faces a considerable threat considering the increasing power and organisation skills that the PCC currently possesses (Freire, 2014).

Nonetheless, it could be that the reduction in homicide rates observed in São Paulo is due to more than one causal chain. Intuitively, one might think that because of better policing, there is an increased probability of a criminal getting caught, and so we should expect a decrease in crime rates given that the expected value of a crime is lower. However, another possibility to account for part of the effect observed in our study is the very empowerment of the PCC itself. If a sizeable number of homicides are drug-related and gang-related—specifically due to gangs competing for turf—then a reduction in homicide rates can be expected when we observe a monopoly in drug trafficking. This alternative causal mechanism works as follows: because of more efficient policing, the incarceration expectation of one who commits a crime is higher; because the criminal has a greater expectation of going to prison, he joins the PCC (either prior to or after being incarcerated), so he is more secure (either inside or outside prison); and finally, because the PCC has a stronger unity, it achieves a monopoly in drug dealing outside prison, resulting in less turf disputes, and consequently, less homicides (Skarbek, 2011).

We also argue in favour of the Synthetic Control Method as a tool to evaluate government policies. This approach offers an intuitive way to assess causality claims when there is only a single treated unit and it can be easily applied in a great number of situations. Given that there is a reasonable number of potential cases in the "donor pool", a synthetic control can be meaningfully compared to the actual case. In this way, the technique allows the researcher to use the potential outcomes framework even in unusual conditions.

Future research can extend our findings in a number of ways. First, it would be interesting to test whether other criminal activities have been affected by the state government policies we

mentioned previously. Since property crimes are pervasive in São Paulo, scholars could evaluate the causal link (or lack thereof) between public policies and the incidence of theft or robberies. Unfortunately, several states in Brazil do not publish time-series data for property crime, so we could not use the Synthetic Control Method for that dependent variable. As more data become available, this seems to be a good topic for scholars. Also, micro-level studies are needed to clarify the mechanisms behind São Paulo's homicide reduction. Due to the shortage of data on targeted policies, qualitative research may explain what the motivations, successes and shortcomings of São Paulo's recent security measures were. Further research could provide insights into how public policies work and, hopefully, help public authorities to design more effective policies against crime.

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