Evaluating the Effect of Homicide Prevention Strategies in São Paulo, Brazil: A Synthetic Control Approach

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Abstract

Although Brazil remains severely affected by civil violence, the state of São Paulo has made significant inroads into 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 total impact of state policies on homicide rates currently exists. The present article fills 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 the synthetic counterfactual, with about 20,000 lives saved during the period. The theoretical usefulness of the Synthetic Control Method for public policy analysis, the role of the Primeiro Comando da Capital as a causal mediator, and the practical implications of the security measures taken by the São Paulo state government are also discussed.

Keywords: Brazil, homicides, PCC, synthetic control, urban violence

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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, 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, the highest incidence rates of intentional homicides on the planet (Waiselfisz, 2014; 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). Murder rates have almost doubled over three decades of democracy, jumping from 15 homicides per 100,000 people in 1985 to roughly 29 per 100,000 in 2012 (Waiselfisz, 2014).[2]

São Paulo has traditionally occupied a key position in Brazil's violence statistics. It is the country's richest and most-densely populated state, and in the 1990s its homicide rate 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 São Luiz and Jardim Ângela had respectively 103 and 116 violent deaths per 100,000 residents (Cardia et al., 2003, pp. 8), figures that placed them amongst the deadliest neighbourhoods on the globe (World Health Organization, 2015).

Nevertheless, the state of São Paulo has experienced a drastic reduction in homicides during the last decade or so (Camargo, 2007). The decline is so remarkable that some authors have called it "the great homicide drop" (Goertzel and Kahn, 2009). The city of São Paulo, which is currently home to about 11 million inhabitants, provides a telling example. Over a span of only seven years (2000–2007), the number of annual violent deaths in the capital fell from 5,979 to 1,311, a 78% decrease.[3] Remarkably, Brazil's largest city became the safest capital in the country (Waiselfisz, 2011).

[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://goo.gl/x0pHac (in Portuguese). Access: January, 2016. In this article, I avoid these issues by using obituary data instead of police records.

[3] The homicide statistics cited in this 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: March, 2016.

São Paulo's success should be attributed to local factors. From 1999 onwards, the state government created or expanded a number of policies that have arguably contributed to the decrease in criminality. In a move coherent with the basic tenets of the economics of crime (e.g. Becker, 1968; Cornish and Clarke, 2014), the administration increased the certainty and the intensity of punishment to discourage potential offenders. Amongst other measures, the government implemented strict gun control policies (Goertzel and Kahn, 2009; Nadanovsky, 2009), raised incarceration rates (Salla, 2007), and imposed harsher sentences on those convicted of a crime (Carvalho and Freire, 2005).

But whereas several authors acknowledge the effectiveness of these policies, few quantitative studies have gone beyond statistical correlations to justify their arguments. In the case of São Paulo, a major difficulty is separating the state's particular time trend to that of Brazil. Ideally, one should compare São Paulo to a control case that shares the same characteristics of the existing state, except that it has not been subjected to the specific set of policies implemented by the São Paulo government. This thought exercise, which emulates the logic of a controlled experiment (Angrist and Pischke, 2008; Imbens and Rubin, 2015; Holland, 1986; Morgan and Winship, 2014), would allow practitioners to untangle the effects of homicide reduction programmes from other potential confounders.

In this paper, I employ the Synthetic Control Method (henceforth SCM) to approximate this experimental ideal and measure the total causal effect of post-1999 public policies on São Paulo homicide rates. The method consists of creating an artificial counterfactual to estimate the impact of a given intervention on a unit of interest. SCM has gained widespread acceptance in many fields, 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 studies (Hinrichs, 2012), and public health science (Heim and Lurie, 2014). However, SCM has rarely, if ever, been used to evaluate homicide prevention strategies in Brazil. SCM is related to other popular causal inference tools such as differences-in-differences (Angrist and Pischke, 2008; Bertrand et al., 2004; Card and Krueger, 1994; Imbens and Wooldridge, 2009) and matching estimators (Dehejia and Wahba, 2002; Ho et al., 2007; Rubin, 1973, 2006; Stuart, 2010). SCM was specifically designed for situations where there is only one treated unit of interest, no readily-available counterfactual, and no certainty as to whether the treated and the control units follow parallel trends after the intervention (Abadie and Gardeazabal, 2003; Abadie et al., 2010, 2011, 2014).

I find that from 1999 to 2009, about 20,000 lives were saved in São Paulo. When compared to a synthetic counterfactual, São Paulo's actual homicide rates were less than 50% of what would be expected in the absence of policy implementation (15 versus 32 homicides per 100,000 people). Additional tests confirm the robustness of the results and indicate a 96.3% chance of a true causal effect in the intervention period.

The article proceeds in four sections. Section 2 discusses how deterrence provides a useful framework to understand the reduction in homicide rates in the state. I also examine an alternative hypothesis for the drop in crime in São Paulo – the rise of the Primeiro Comando da Capital – and argue that the prison gang should be regarded as a mediator, not as an independent cause of homicide reduction. Section 3 presents a justification for, and a technical explanation of, the Synthetic Control Method. Section 4 describes the data used in this paper. Section 5 discusses the results of the models, and section 6 offers some concluding remarks.

2 Theoretical Background

2.1 Deterrence and the Drop in Homicides

A myriad of explanations have been proposed for the fall in homicide rates in São Paulo. Some authors have stressed the importance of long-term factors on local levels of violence. Mello and Schneider (2010) claim that the ageing of the São Paulo population explains part of the decline in homicides. The shrinking of the proportion of males in the 15–25 age bracket has led to fewer violent deaths at both state and city levels. Hughes (2004) argues that São Paulo's spatial segregation patterns have had a lasting impact on murder rates. In his view, social inequalities are largely responsible for the dispersion of crimes across the state, and although rich areas in São Paulo are virtually unaffected by violence, poor suburbs bear the brunt of the homicides.

Structural variables have likely been important, but the role of public policies in the reduction of violence should not be underestimated. 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 expanded those measures and taken a notoriously tough stance on crime (Feltran, 2012a).

Methods of crime prevention have received considerable attention from the authorities. In 1999, the state administration created a new system for intelligence, Infocrim. The system gathers geocoded information on homicides and its purpose is to map the most important "hot spots" of criminal activity in the state. The government also developed a new photo database, Fotocrim, to speed up the process of facial recognition of criminals (Mello and Schneider, 2010, p. 3).

Apart from investment in police intelligence, the government has significantly increased incarceration rates in the past decade (Salla, 2007). São Paulo currently holds around 200,000 convicts in prison (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 become 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).

Importantly, the state government has successfully enforced the banning of gun possession in São Paulo, and studies show that this policy has had a significant effect on criminality (Goertzel and Kahn, 2009; Kahn and Zanetic, 2005). Moreover, the effect of the Brazil's 2003 National Disarmament Act was especially pronounced in São Paulo (Cerqueira and Mello, 2013).

This set of policies is largely in line with the rational choice theory of crime (e.g. Becker, 1968; Cornish and Clarke, 2014; Stigler, 1974). The rational choice approach presents a sharp departure from structural criminology. Structuralists have long argued that criminal tendencies derive from the social environment in which an individual finds him/herself. Two of the most prominent strands in this literature are the social disorganisation (Faris, 1948; Shaw and McKay, 1942) and social control theories (Gottfredson and Hirschi, 1990; Hirschi, 1969). Social disorganisation scholars affirm that delinquency is an outcome of local structures such as neighbourhoods or extended families (Jobes et al., 2004, p. 115). Stable and cohesive communities induce their members to become law-abiding due to the ability to quickly solve common problems and the enforcement of shared norms (Bursik, 1988, p. 521). Conversely, frayed social structures – such as heterogeneous groups or unstable families – have a negative influence on individual behaviour (Bellair, 1997; Kornhauser, 1978; Shaw and McKay, 1942). In this framework, the most effective crime-fighting measures are those which foster family ties, social cooperation, and community attachment (Nelson et al., 1990; Rose and Clear, 1998; Sampson, 1988; Sampson and Groves, 1989).

Similarly, the social control theory posits that social ties diminish individual tendencies toward criminal behaviour (Goode, 2008; Gottfredson and Hirschi, 1990; Hirschi, 1969; Matsueda and Heimer, 1987; Wiatrowski et al., 1981). Control theory starts from the Hobbesian assumption that every individual is capable and willing to engage in criminal activities (Hobbes, 1651), and advocates that people only restrain their self-interest through social learning processes (Gottfredson and Hirschi, 1990, p. 15). In this approach, the major – if not the only – cause of criminal activities is *low self-control* (Goode, 2008; Gottfredson and Hirschi, 1990). Scholars of this tradition suggest that parenting practices are crucial for inhibiting criminal activities amongst youths (Akers and Sellers, 2013), and school bonds play an important role in reducing early delinquency (Sprott, 2004; Sprott et al., 2005).

In contrast to the ecological theories described above, the rational choice school posits that criminals are motivated by utilitarian cost-benefit analysis (Cornish and Clarke, 2014; Piquero, 2012). Individuals calculate what the possible trade-offs are between the benefit of the committing a crime and the risk of being punished for it. Criminal offenders, therefore, are in no way different from non-criminals: the only difference between them is their *choices* (Nagin, 2007). To reduce criminality, policy-makers have to ensure that the costs of committing a crime outweigh the eventual utility an individual derives from it.

The São Paulo administration implemented policies that fit the rational choice understanding quite well. Gun control has an important effect as a general deterrent, as it reduces the likelihood that someone who has not engaged in crime decides to do so in the future (Andenaes, 1974; Stafford and Warr, 1993). In turn, the rise in incarceration rates and the adoption of severe punishment for prisoners are typical examples of specific deterrence, a strategy that aims to reduce *future* crime by imposing harsher sanctions on offenders (DeJong, 1997; Smith and Gartin, 1989). But how well have these policies performed over time?

The results suggest a favourable outlook. Compared to other Brazilian states, São Paulo is an outlier when it comes to homicide rates. Despite the fact that crimes against property have remained relatively stable over the last decades,[4] the number of violent deaths per 100,000 inhabitants shows a steep downward trend. Figure 1 presents the evolution of homicide rates in São Paulo in comparison with the Brazilian average.

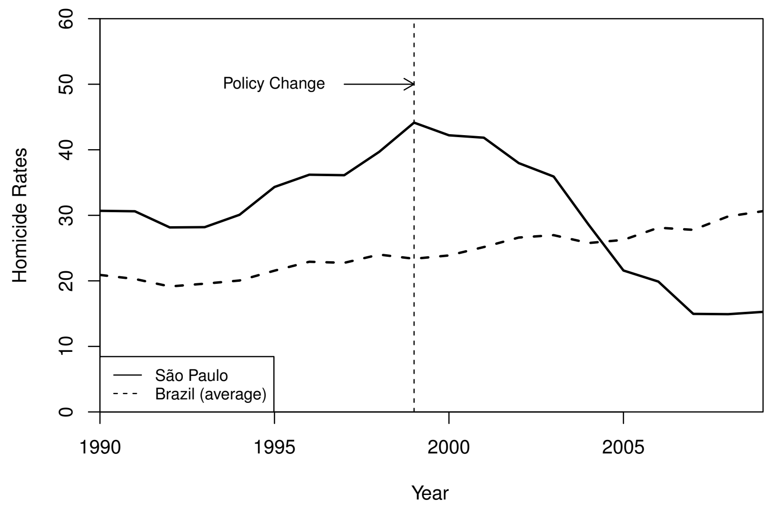

Figure 1: Homicide Rates per 100,000 Population – São Paulo and Brazil (Excluding São Paulo)

Nevertheless, it is difficult to know 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 may be large interaction effects amongst different public security measures. Therefore, at the moment it is not possible to disentangle micro-level causes from macro effects. But the aggregated impact of the anti-crime policies can be correctly identified if there is no other variable in the causal path leading from the policies mentioned above to our dependent variable (state homicide rates). I argue below that this type of estimation is feasible for the São Paulo case. To back this claim, I suggest that a competing explanation for the homicide drop in São Paulo – the rise of the PCC – interferes only with the direct effect of the policies on crime, but not with their *total* effect. In this sense, the Synthetic Control Method provides a plausible identification strategy for my question of interest.

[4]Recent data on property crimes in São Paulo can be seen at http://www.ssp.sp.gov.br/novaestatistica/Pesquisa.aspx (in Portuguese). Access: July 2016.

2.2 Alternative Explanation: The Emergence of the PCC

A recent hypothesis attributes the decrease in violent deaths in São Paulo to the *Primeiro Comando da Capital* (First Command of the Capital, henceforth PCC) (Biondi, 2010; Dias, 2009a, 2011; Feltran, 2010, 2012a; Willis, 2015). The PCC is a prison gang that emerged in the early 1990s as a response to the demands of a growing prison population. The PCC provides personal security and financial assistance to their members and affiliates. The gang's internal statute clearly declares that "[…] those who are in liberty [must contribute] to the brothers inside prisons [PCC members] through lawyers, money, help to family members and prison outbreak operations" (Folha de São Paulo, 2001).

A group of scholars affirms that the PCC significantly contributed to the reduction in violence mainly through the São Paulo prison system. At least since the mid-2000s, these authors argue that the PCC has been able to emerge as an undisputed mediator and solve conflicts between inmates. Dias (2009b, p. 83) writes that "[…] when unable to constitute a universal source of regulation, the official law leaves gaps which are filled by informal instances – such as the Primeiro Comando da Capital (PCC), in the prisons of São Paulo." The gang has implemented informal courts that resemble state institutions, and those meetings have progressively replaced other forms of popular justice such as lynchings or the hiring of target killers (Feltran, 2012b, p. 3). Moreover, the *Comando* has developed a series of assertive ways to verbally terrorise inmates. Since the PCC's threats are credible, the group is able to impose discipline.

There has been a vigorous debate over whether the PCC has had a significant impact on street-level violence rates. A few authors see the PCC as the sufficient condition behind the homicide rates decline across São Paulo state (Biondi, 2010; Dias, 2009a, 2011), whilst others take a more nuanced view of the role of the prison gang. Willis (2015) describes how both the PCC and the police forces mediate conflicts in certain areas of the São Paulo capital. He posits that this "killing consensus" is a relevant factor in the homicide reduction nexus.

Recent econometric works, however, provide little evidence that the PCC is the most important driver of the drop in murders. Marcelo Nery tested this argument using geo-referenced data and found no convincing results in favour of the "PCC thesis" (BBC, 2016). New research by Biderman et al. (2016) uses anonymous calls to a crime hotline as a proxy for PCC presence in São Paulo city favelas. The authors find some support for the idea that the gang reduces lethal violence in areas under its control, but PCC presence corresponds to only a minor drop in violent crime. Although the PCC impact is not negligible, the gang is not a sufficient condition for the homicide decline.

Another counter-argument to the PCC thesis is that homicides also decreased in areas where the PCC does not exert control. Firstly, descriptive statistics show that the decline in violent deaths started *before* the PCC's expansion period.[5] Secondly, the drop in crime was evenly distributed throughout the state: urban and rural areas, small and large cities alike experienced fewer murders.[6] Finally, Peres et al. (2011) note that violent death rates decreased in *all* age groups and social classes in the city São Paulo, particularly amongst poor, male youth. Hence, cohorts that do not correspond to typical PCC members (such as the elderly or middle-age females) are also less affected by violence.

In a nutshell, it seems that the influence of the PCC over physical violence has been overstated. While there is no reason to discredit the in-depth exploration of violence dynamics described in recent ethnographic works, their arguments have proved problematic to generalise. Furthermore, the drop in homicides coincide exactly with the expansion of a number of public policies targeted at violent crime, and it has affected the state as a whole. It is unlikely that the PCC – which is rather underfunded for its size[7] – could have achieved such a deep penetration into society.

2.3 Causal Paths, Mediators, and Total Effects

A methodological issue remains. If we are to estimate the causal effect of the public measures on the crime rates, how should we proceed? I have noted above that the specific impact of micro-level policies cannot be evaluated due to lack of data. Nonetheless, it is theoretically possible to estimate the *total* effect of policies on crime.

The difference between direct and total effects can be understood as follows. The direct effect captures the sensitivity of a dependent variable Y to changes in X when this relationship is not mediated by any other variables in the model. Holding all factors constant, the direct effect is a causal chain of length one (Sobel, 1987, p. 160) and could be described simply as $X \rightarrow Y$. In turn, the total

[5] As shown in figure 1, São Paulo's homicide rates started to drop in 1999. The PCC consolidated their power in the prison system only in the mid-2000s (Dias, 2011).

[6] See: http://www.fenapef.org.br/27764/ (in Portuguese). Access: July 2016.

[7] A Parliamentary Commission of Inquiry has stated that the PCC earns about 16 million Brazilian Reals per month, which amounts to approximately 60 million US dollars per year (see: http://goo.gl/FwhPa3 (in Portuguese). Access: July 2016). Given the size of the organisation and its undisputed position as the leading crime syndicate in São Paulo, the figures are rather small. As a comparison, Mexico's Sinaloa Cartel profits about 3 billion dollars per year, a sum comparable to the annual earnings of Netflix or Facebook (see: http://nyti.ms/1B09qyV. Access: July 2016).

effect can be defined as $P(Y_x = y)$, that is, "the probability that response variable Y would take on the value y when X is set to x by external intervention" (Pearl, 2001, p. 1572). The total effect is the sum of direct and indirect (or mediated) effects.

In our case, gun control, incarceration, and police intelligence have likely had a direct effect on homicides. Taken together, these variables comprise a direct aggregate policy effect. The omission of a variable measuring the impact of the PCC could bias such an effect, but not interfere with the *total policy effect*. This point is worthy of further consideration. The total policy effect would be unbiased under the assumption that the PCC is in fact a *mediator* between the public policies and the homicide rates, even if the gang's impact over the violence levels is not particularly large.

Although this argument has rarely been posited in such terms, this position is largely supported by the qualitative literature on the PCC. Fieldwork research generally traces the group's origins and growth to the rising incarceration rates in São Paulo and the need for protection amongst prisoners (Dias, 2011; Manso and Godoy, 2014). Like other prison groups, the PCC would only mobilise resources to provide welfare and act as an arbitrator under the condition that the certainty of punishment by the state is high (Skarbek, 2011; Freire, 2014). Had the state not increased the costs associated with crime, the prison gang would not have expanded their reach, or even been created in the first place. Hence, the impact of the PCC on street-level violent deaths – if it exists – can be safely assumed to be a mediator effect.

Whereas it would be interesting for researchers to separate these types of effects and isolate the PCC from the other causal outcomes, such estimation is not possible at the state level. However, as these measures were implemented throughout São Paulo state at roughly the same time, their combined effect is computable even though their individual direct effects are not. To do so, it is only necessary to contrast the treated unit (São Paulo) with a counterfactual without the time-assigned treatment (1999 onwards) and evaluate the aggregated effect of the public policies.

This analysis can be estimated in a consistent manner with the Synthetic Control Method. In the following sections I describe how the method creates a valid counterfactual case under a certain set of assumptions. The assumptions are: 1) the PCC is an outcome, not a cause of the crime-targeting policies; 2) the model does not include unnecessary control variables; 3) interpolation bias is not very severe because the cases in the "donor pool" are relatively similar to the treated unit.

3 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. This practice 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. Also, the researcher can still specify what control cases enter the "donor pool." In this sense, qualitative expert knowledge can be incorporated in the estimation via the selection of cases. In the case of São Paulo, the natural candidates for control cases are the 26 remaining Brazilian states.

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. SCM can be understood as a combination of matching with differences-in-differences. SCM uses matching as a flexible pre-processing tool to reduce imbalance between treated and control units (Ho et al., 2007; Rubin, 1973, 2006).[8] But unlike matching, SCM deals with only one treated unit over time. Therefore, the method can also be interpreted as a semi-parametric extension to differences-in-differences estimators (Abadie, 2005). However, SCM relaxes the most problematic assumption of differences-in-differences: it does not suppose that both treated and control units follow parallel trends in the whole period. By combining semi-parametric matching with differences-in-differences, SCM provides a rigorous yet versatile method to evaluate time-dependent treatment effects.

SCM has an intuitive interpretation. Although numeric summaries and other statistics can be obtained from the model, a simple time series graph is usually enough to assess the results. The causal effect is the difference between the treated and the synthetic cohort. The larger the post-treatment gap, the stronger the treatment impact.

[8] The synthetic case is thus constructed as a combination of possible controls, and those that are more similar to the treated unit receive more weights. The weights make explicit the contribution of each separate case to the synthetic control, what also increases the transparency and reliability of the counterfactual (Abadie et al., 2014).

As with all types of observational studies, SCM can also suffer from omitted variable bias. One can never be sure whether all required confounders have been included in a given model. However, the graphical output of the SCM helps diagnose the presence of large disparities between treatment and control cases. If the trends follow similar paths during the control period, it provides some indication – albeit only informally – that omitted variable biases are not driving the output. This bias can also be mitigated with expert knowledge. Econometric studies show that the inclusion of a large number of covariates and post-treatment variables to correct for omitted variables bias can actually *worsen* the problem (Achen, 1992, 2002; Clarke, 2005, 2009; Pearl, 2009). This is particularly true for matching methods. Authors have noted that "over-matching" can lead to severe statistical bias (Baser, 2006; Brookhart et al., 2006; Marsh et al., 2002). In this regard, the most plausible solution seems to be attention to the trends and sensible selection of control variables. As I discuss in the next section, the covariates included in this paper are some of the most robust quantitative predictors of homicides.

Furthermore, placebo tests can be run to test the robustness of the findings. For instance, researchers can include "in-time placebos," dates under which the treatment *did not* occur. Results should change only in the period when the treatment starts and not at any other point in time. Moreover, scholars can also add "in-space placebos" to their models. This test consists of adding different members of the donor pools into the models to see if the estimation varies (Abadie et al., 2014). Finally, one can also compare the effects of the treatment of interest by creating a distribution of synthetic cohorts, where every unit (treated or not) is matched with a specific synthetic control case. The parameter of interest should still be relevant. I employ all of these tests in this article.

Formally, the method works as follows.[9] Let $j = 1, \dots, J + 1$ be a series of units in periods $t = 1, \dots, T$. In our case, the units are the 27 Brazilian federal states and the time period spans from 1990 to 2009. 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, *i.e.* the 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 treatment (1990–1998). 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 (1999–2009). An important assumption is that the

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

treatment has no effect on unit i before the date of intervention, therefore, the values for São Paulo with and without the policy interventions are the same for the pre-treatment period (1990–1998). In formal terms, $Y_{it}^{I} = Y_{it}^{N}\ \forall t < T_0$. 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, 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}, the effect of the "treatment" (homicide reduction policies), for the state of São Paulo for all $t \geq T_0$, that is, from 1999 to 2009. However, we cannot observe São Paulo *without* those policies, as there is no way for the state to have and not have the intervention at the same time. This is what Holland (1986) calls the "fundamental problem of causal inference:" only one of the outcomes of interest is measurable at any given time.

But although we cannot accurately know how São Paulo would be without the treatment, we can approximate it by using a weighted average of the remaining Brazilian states 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 control variables 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 (error term). Basically, what SCM tries to do is to match Z_i, the control variables, and the pre-treatment Y_{it} of São Paulo (1990–1998) so that μ_i is matched as a result.

To state again clearly, synthetic São Paulo is the weighted average of the other 26 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 São Paulo 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 $||X_1 - X_0W||$, subject to the weight constrains. We consider $||X_1 - X_0W||_v = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}$, 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 of choosing V, in this paper, we follow the recommendation of Abadie and Gardeazabal (2003) and choose V^* as the value of V that minimises the root mean squared prediction error (RMSPE) for homicide rates in the entire pre-treatment period (1990-1998).

4 Data

I 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[10] and represent important social and economic factors I wish to control for.

The unit of analysis is State-Year. I 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 yet been published. All data used in this paper come from the same source, the *Instituto de Pesquisa Econômica e Aplicada* (IPEA), a government-led research group.[11]

My dependent variable measures the number of homicides per 100,000 inhabitants, which is the most commonly used unit of analysis for lethal violence. This variable was coded by the Brazilian Health Ministry from obituary records, therefore it is less likely than police files to suffer from intentional misrepresentation.

There are six control variables in the models. *State GDP per Capita* is adjusted in 2010 Brazilian

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

[11]The data are publicly available at http://www.ipeadata.gov.br/. The original data files have also been added to https://github.com/danilofreire/homicides-sp-synth for reproducibility purposes.

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. *Natural Logarithm of Population* represents yearly projections of the state population. Since Brazil only runs a census every 10 years, 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 that I created specifically for this study. It was coded by simply taking the number of individuals classified as extremely poor by the IPEA and dividing this number by the state's total population.[12]

5 Analysis

5.1 Main Model

I construct the synthetic cohort (*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 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.*, the six out of the 27 possible cases that received 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. 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.

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

[12] *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 online. See the supplementary appendix for further details on how to replicate this study.

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

the data I 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 see that Synthetic São Paulo has very similar coefficients to those of the treatment unit. Moreover, the synthetic control clearly 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 the results since the variables that received zero weight were discarded from the 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

The 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. 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 observe 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 I noted in the first part of this text.

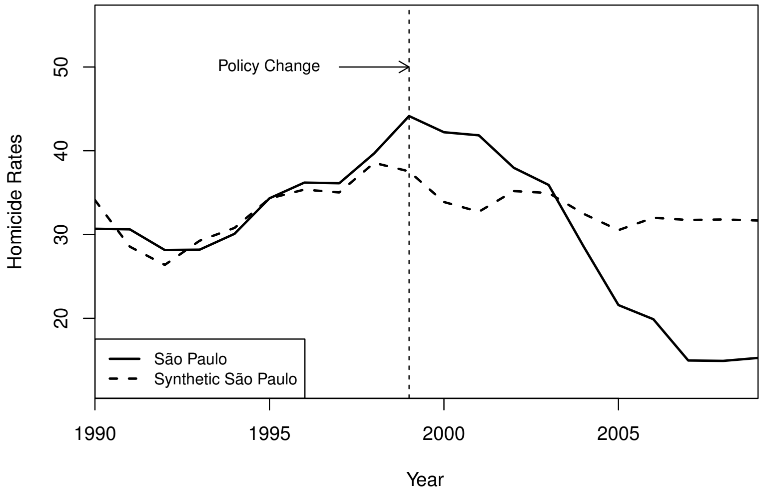

Figure 2: Trends in Homicide Rates: São Paulo versus Synthetic São Paulo

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 is not a single peak in homicide rates after the policies have been put into practice. I interpret that as strong evidence in favour of the public policies.

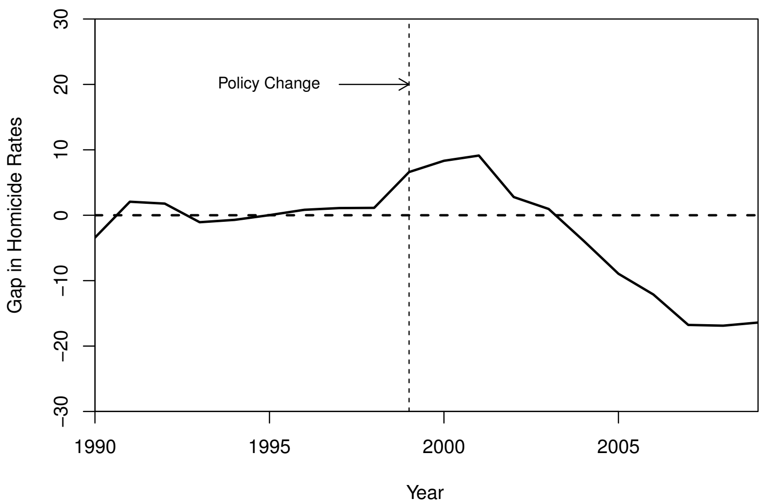

Figure 3: Homicide Rates Gap between São Paulo and Synthetic São Paulo

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[13] It is important to mention that the homicide rate in São Paulo continues to drop by the year, while the same is not happening in the rest of the country.

5.2 Robustness Checks

To further analyse the findings, I run five robustness tests. I 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 the main results could be put into question. The result of this placebo test can be seen in Figure 4. When I run the optimization 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.

[13] My estimate of lives saved by the policies implemented in São Paulo is done as follows. I consider the years after policy implementation (1999-2009), then I sum the number of homicides in São Paulo in that period. This gives us 124,077 homicides between 1999 and 2009. I do the same procedure for the Synthetic São Paulo; I 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 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. The result is 20,331 lives saved.

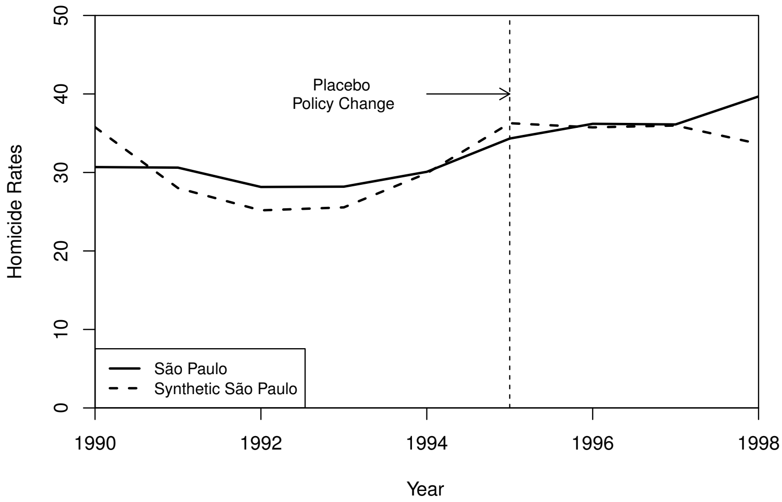

Figure 4: Placebo Policy Implementation in 1994: São Paulo versus Synthetic São Paulo

I also conducted a leave-one-out robustness test. In this test I 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.

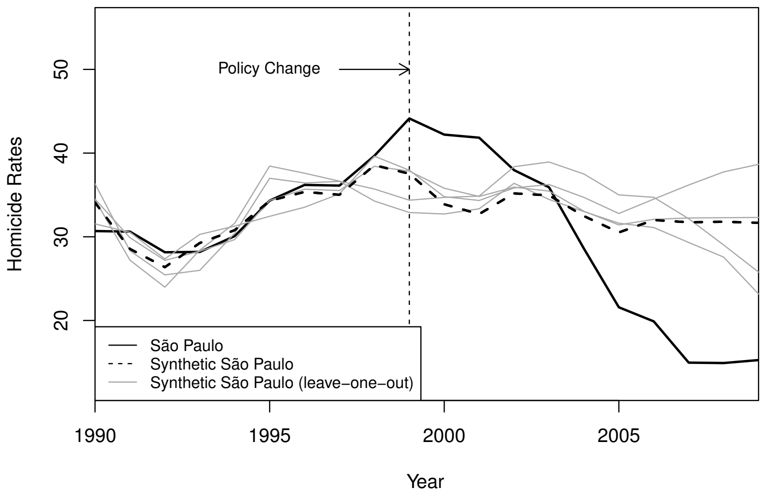

Figure 5: Leave-One-Out Distribution of the Synthetic Control for São Paulo

Figure 6 shows the difference in homicide rates between the treated units and their synthetic controls. Here I include not only São Paulo and its simulated counterfactual, but placebo synthetic controls for the other 26 Brazilian states. We observe 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.

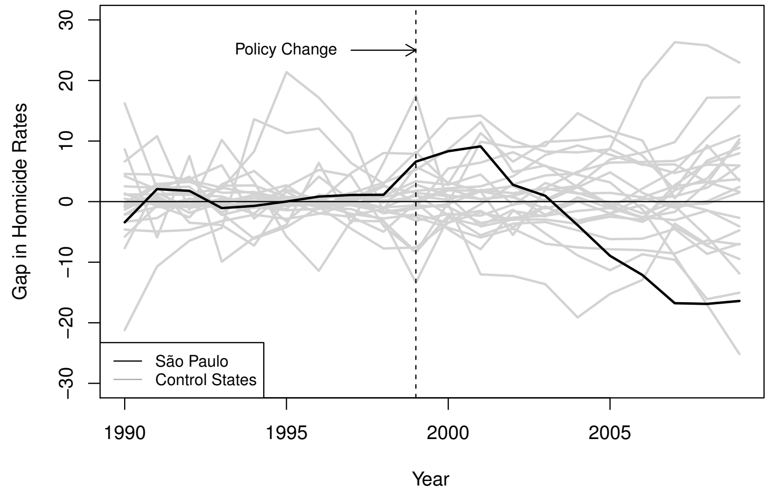

Figure 6: Permutation Test: Homicide Rate Gaps in São Paulo and 26 Control States

Figure 7 uses a strict threshold for the simulated synthetic controls. The test is similar to the one presented in figure 6, and it consists of simulating placebo synthetic control for all Brazilian states. However, the graph features cases in which the mean squared prediction error is no higher than twice that of São Paulo. That is, only placebos with very good fit were selected for the analysis (Abadie et al., 2010, pp. 503). In this group, the negative gap for the homicide rate São Paulo is by far the most relevant, providing further evidence for the original results.

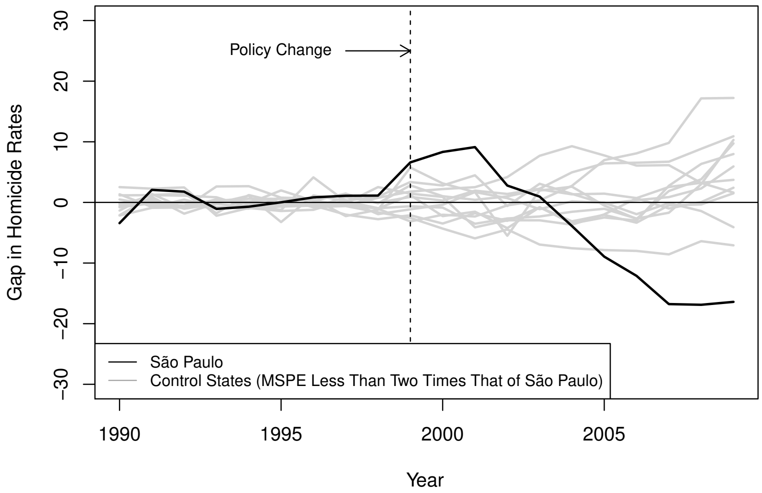

Figure 7: Permutation Test: Homicide Rate Gaps in São Paulo and Selected Control States

Lastly, I estimate another synthetic control using another approach. Here, I employ a Bayesian structural time-series model to verify the stability of the model results (Brodersen et al., 2015). The inference procedure is similar to that described in section 3 and it also consists of matching pre-treatment values of the unit of interest, São Paulo, to other potential control states. However, in this model only the time trends of the dependent variable are matched. In a sense, this is closer to a traditional "differences-in-differences" approach, but allowing the effect of unobservable variables to vary over time (Abadie et al., 2010, p. 494).

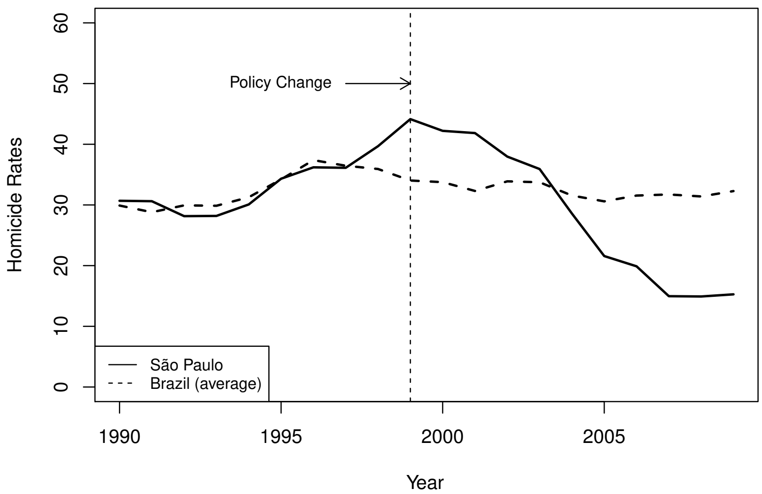

Figure 8: Bayesian Structural Time Series Model: São Paulo and Synthetic São Paulo

The model shows that in 2009 we should have expected São Paulo to have a homicide rate equal to 32.3 deaths per 100,000, but we observe only 15.2. Thus, the actual rate in São Paulo corresponds to only 47% of the expected counterfactual. The method also generates an estimate for the probability of causal effect. The calculations indicate a 96.3% chance of a causal impact in the period. In this sense, it is extremely unlikely that the results are a statistical fluke.

6 Conclusion

As I have hopefully 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, I suggest that their aggregate impact is 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. This as an encouraging result, as it suggests that governments can make progress in reducing crime with the 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 my findings.

I 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. Assuming 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 the present 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 I 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 I could not use the Synthetic Control Method for that dependent variable. As more data become available, this will create an interesting opportunity for investigation. Secondly, micro-level studies are needed to clarify the mechanisms behind São Paulo's homicide reduction, and isolate direct from indirect effects of each individual policies. 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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