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AN ANALYSIS OF DISCRIMINATION BIASES IN HOMICIDES COMMITTED BY THE POLICE IN SÃO PAULO

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Tese referente ao programa de Pós-Graduação em economia da Faculdade de Economia da Universidade Federal de Juiz de Fora como requisito para obtenção do grau de doutor.

Orientador: Prof. Dr. Eduardo Almeida

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RESUMO

Eventos recentes desencadearam uma série de discussões sobre vieses de discriminação no comportamento policial. Um intenso debate vem discutindo se as disparidades raciais observadas no comportamento policial se devem a viés de discriminação racial ou estatístico. Esta tese tem como objetivo lançar uma luz sobre o tema no Brasil. A literatura existente tem o seu foco em examinar essa questão para países desenvolvidos, tais como EUA e Canadá. Até onde vai nosso conhecimento, não há outro estudo sobre esse tema na literatura para países menos desenvolvidos. Os dados referentes a boletins de ocorrência policial foram compilados no nível de incidente para os anos de 2013 a 2021. A identificação dos dois vieses de discriminação é feita por meio de um modelo multinível de resposta binária, em que se avaliam as diferenças na escolha do policial quando este possui ou não uma clara visibilidade da vítima. Visando explicar ao máximo as diferenças entre os indivíduos, adicionaram-se variáveis de controles relevantes referentes a características individuais e sociodemográficas do ambiente. Os resultados obtidos revelam que não se encontram evidências de viés de discriminação racial, mas encontram-se evidências de viés de discriminação estatístico na abordagem policial tanto na capital paulista quanto na região metropolitana de São Paulo.

PALAVRAS-CHAVE: viés de discriminação racial; viés de discriminação estatístico; polícia; crime.

ABSTRACT

Recent events have triggered a series of discussions about racial discrimination in police behavior. An intense debate has been held to discuss whether the racial disparities observed in police behavior are due to racial or statistical discrimination bias. This dissertation aims to shed some light on the subject in the Brazilian context, specifically in the city of São Paulo. Previous literature has focused on examining the problem for more developed countries, such asUSA and Canada. As far as we know, there is no other study analyzing the problem for less developed countries. By collecting microdata from the police reports at the incident level for the years 2013 to 2021, we propose an identification strategy aimed at isolating the effects of racial bias and statistical bias discrimination in the police behavior through a binary response model, based on the visibility condition of the victim that the police officer has when committing homicide. Control variables that explain important individual characteristics and socio demographic variables regarding the environment in which the homicide happened were inserted in the analysis, aiming to explain as much as possible the differences between individuals. The results revealed no evidence of racial discrimination in the police behavior in the metropolitan area of São Paulo, however we found evidence of statistical bias discrimination.

KEY WORDS: racial bias discrimination; statistical bias discrimination; police; crime.

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SUMMARY

1. INTRODUCTION

The current sociology literature defines racism as the belief of superiority that an individual or a group of individuals has towards another group, usually a minority, but that is not always the rule. In other words, the behavior of an individual towards another one is predetermined by the biological features of the latter. The social and moral traits of a person who experiences racism are usually predetermined by its inborn characteristics.

The Social Labeling Theory emerged in the 1960s in the United States during a turbulent period in the history in which movements led by Martin Luther King were fighting for racial equality. The Social Labeling Theory proposed the idea that some individuals are labeled as criminals because of some features, for example, black individuals (usually those who belong to the lowest stratum of the social pyramid) are identified as criminals just because they are black.

According to Foucault (1995), an ideal criminal system would be one that equitably affects all segments of the population, reaching equally all individuals based only on their behavior. However, in practice, especially by the influence of the media, one perceives an excessive use of police force in different strata of society. The fact that an individual is poor, black, or Native Americans causes him to be seen as a potential criminal.

Movements such as Black Live Matters have raised the attention to the disparities in the number of police violence against black individuals in the United States. Given an example of racial disparities observed in police-civilian interaction data, Fryer (2019) explored the New York City’s Stop, Question and Frisk data, which consist of approximately 5 million interactions between civilians and police officers between 2003 and 2013 in NYC. Summary statistics showed that 58% of all police-civilian interactions included a black civilian. If the police officer were randomly stopping individuals, this percentage should be close to 25.5% (New York City’s population). Moreover, Fryer (2019) points out that black people and Hispanics younger than 24 years old were more than 50% likely to experience some form of use of force in interactions with the police.

Becker (1957) was the first person to propose an economic model for discrimination. The author defined the concept of preference-based discrimination, or racial bias discrimination (RBD), when a group of individuals discriminate against a minority group albeit they do not receive any monetary benefit from doing so.In contrast to this idea, Arrow (1973) introduced the concept of statistical bias discrimination (SBD).

In circumstances of uncertainty, a group of individuals may discriminate against a minority group if the latter believes that discrimination will lead to a better outcome.

A number of recent papers (Knowles, Persico and Todd, 2001; Grogger and Ridgeway, 2006; Antonovics and Knight, 2009; Coviello and Persico, 2015; Horrace and Rohlin, 2016; West, 2018 Fryer, 2019; Weisburst, 2019; Gonçalves and Mello, 2020; Lieberman, 2020) empirically analyze if those observed disparities consist of some form of racial profiling[1] against minority groups that could be characterized as a form of prejudice, which, in turn, may be motivated by racial bias, statistical bias[2] or a combination of both.

Understanding the driving factors behind the motivation of the police officer's decision to discriminate against a group of individuals is crucial for designing effective public policies to change this pattern.

1.1 *Motivation*

The number of fatal encounters between civilians and police officers in 2019 in the United States was estimated by the Global Burden of Disease Study 2019 Police Violence US Subnational Collaborators (2021) to be 1,150 deaths (with a confidence interval of 95% in the range of 998 to 1,310). Edwards, Lee and Esposito (2019) suggest that one in every 1,000 black men are killed by the police in the USA, making them two to five times more likely to be killed by a police officer compared to white men.

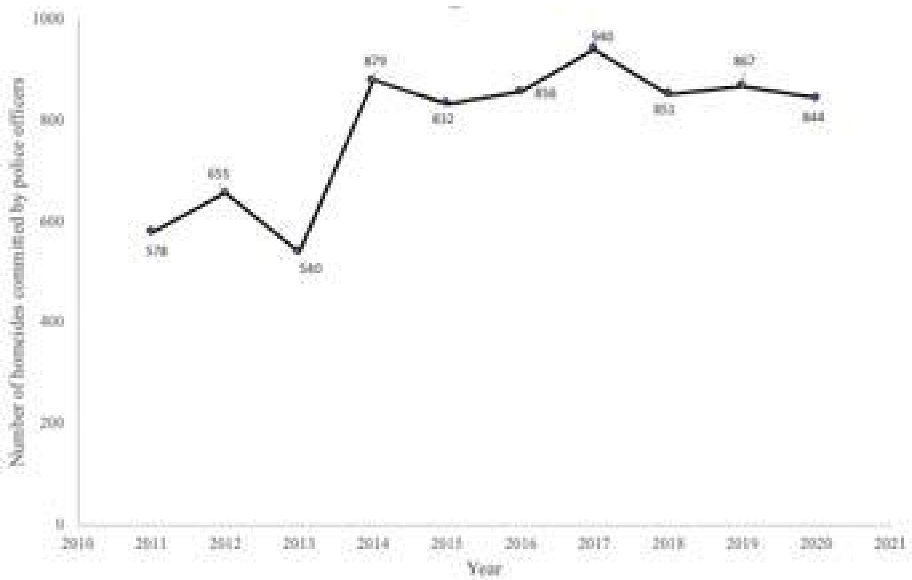
To the best of our knowledge, the empirical literature on the link between discrimination and police behavior is in its majority concentrated in the United States (Knowles, Persico and Todd, 2001; Grogger and Ridgeway, 2006; Antonovics and Knight, 2009; Coviello and Persico, 2015; Horrace and Rohlin, 2016; West, 2018 Fryer, 2019; Weisburst, 2019; Gonçalves and Mello, 2020; Lieberman, 2020), with a few other studies discussing the problem outside the USA (Wortley and Owusu-Bempah, 2009; Andersen et. al, 2021). However, looking at the summary statistics of police lethality, the estimated number of homicides committed by the police task force in Brazil is almost four times the number of homicides committed by the police in the USA. Data from the Fórum Brasileiro de Segurança Pública, a Brazilian non-governmental organization

[1] Racial profiling can be defined as the discriminatory practice by law enforcement officials of suspecting that a civilian has committed an offense based on the race of the individual.

[2] The prior belief of the police officer about a minority group (black individuals, for example) on the statistical bias assumption does not necessarily reflect the reality. For example, a police officer could have a prior belief that black civilians are more likely to be criminals when this belief is false. This characterizes a false prior belief and can be considered a form of prejudice.

dedicated to public security, shows that 4,222 people were killed in police actions only in 2016. The States of Rio de Janeiro and São Paulo were the ones with the highest police lethality rate. Figure 1 shows an evolution of the number of homicides committed by police officers in the State of São Paulo since 2011.

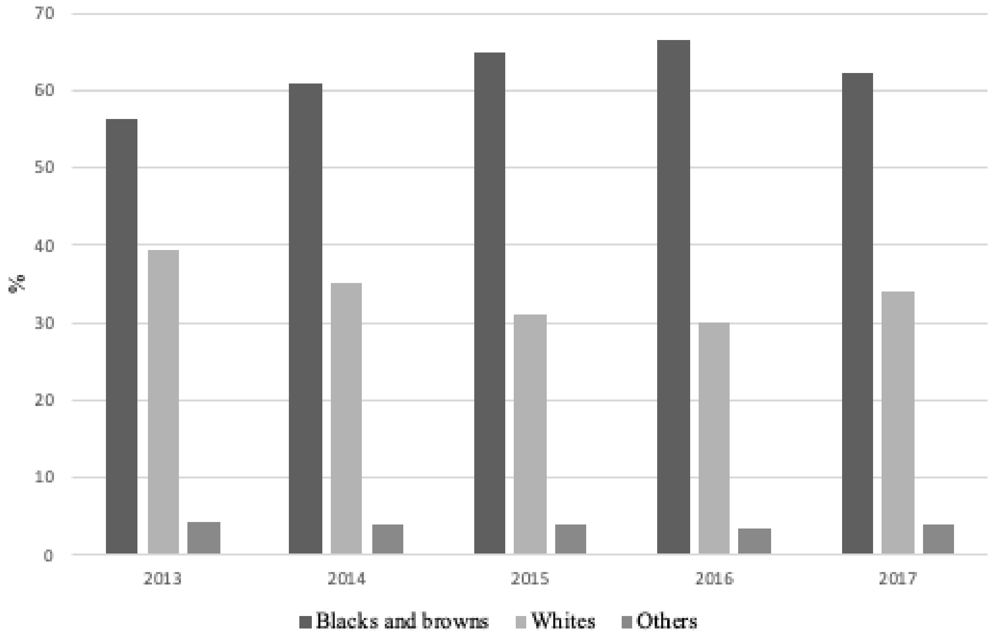
Figure 1: Number of homicides committed by the Police in the State of São Paulo, 2011:2020



Source: Public Safety Office of the State of São Paulo.

One of the main aspects of racial inequality in Brazil is the strong concentration of lethal violence against the black population. When calculated within population groups of black and non-black, homicide rates reveal the magnitude of inequality. In 2016, the homicide rate for black people was two and a half times higher than for non-black people (40.2% against 16.0%). Over a decade, between 2006 and 2016, the homicide rate of black people grew 23.1%. In the same period, the rate among the white population decreased by 6.8%. It is also worth noting that the homicide rate of black women was 71% higher than that of non-black women. Black people are also the main victims of police lethal action, and the predominant racial group of the prison population in Brazil (Cerqueira et al., 2018). The situation regarding police lethality is not different. For instance, data collected from 2013 to 2017, depicted in Figure 2, by the Fórum Brasileiro de Segurança Pública showed that, in average 62.14%, of the victims of homicides committed by police officers in the period were black or brown people.

Figure 2: Racial profile of the homicides committed by the Police in Brazil from 2013 to 2017



Source: Fórum Brasileiro de Segurança Pública.

This dissertation aims to shed some light on the topic in Brazil, specifically in the city and the metropolitan area of São Paulo. Previous literature has focused on examining the problem mainly in the United States, with a few exceptions. To the best of our knowledge, there is no other study analyzing the problem in Brazil.

Based on the definitions of racial bias discrimination (Becker, 1957) and statistical bias discrimination (Arrow, 1973), the main question in this dissertation is: does the race of an individual influence police behavior? And to an extent, does the environment in which the homicide happened have an impact on the police behavior? Evidence of racial bias discrimination (RBD) would be a meaningful change in the police behavior due to the race of the victim, even though there is no increase in the society's welfare measured by the reduction of crime. In other words, the police officer discriminates solely because of the race of the person, despite the fact of not knowing whether the individual is a criminal or not. On the other hand, statistical bias discrimination (SBD) would arise in a context of uncertainty when the police officer makes racial profiling by targeting a group of individuals, based on a prior belief that this group of individuals are more likely to be criminals.

We argue that the environment potentially changes the feeling of security perceived by police officers. Therefore, in a situation of high uncertainty, the police officer might increase the intensity of racial profiling (SBD)[3].Contributing to the current literature of police behavior and discrimination bias (Knowles, Persico and Todd, 2001; Grogger and Ridgeway, 2006; Antonovics and Knight, 2009; Coviello and Persico, 2015; Horrace and Rohlin, 2016; West, 2018 Fryer, 2019; Weisburst, 2019; Gonçalves and Mello, 2020; Lieberman, 2020), we design an empirical strategy that identifies both racial bias discrimination and statistical bias discrimination in police behavior.

In a real scenario, in which the police officer cannot assess whether the civilian is a criminal or not, if evidence of discrimination is found, we do not have any conclusion about the motivation behind the police officer actions. However, in a hypothetical scenario, in which the police officer can tell apart if the civilian is a criminal or not, if we have evidence of discrimination, we can conclude that the police officer has a racial bias behavior if the civilian is not a criminal. Otherwise, if the civilian is a criminal, the police officer has a statistical bias behavior. In other words, identifying the reasons for racial profiling is tricky, in the sense that the econometrician does not observe the perception that the police officer has of the civilian during the encounter.

The benchmarking criminology literature is agnostic about the reasons for racial profiling (Horrace and Rohlin, 2016; Terrill, Alpert, Dunham, and Smith, 2003; Withrow, 2004; Zingraff, Smith, and Tomaskovic-Devey, 2000, Grogger and Ridgeway, 2006). Horrace and Rohling (2016) argue that:

> "*In the absence of racial prejudice, the practice of racial profiling could be attributable to optimal police behavior in a model of statistical discrimination*." (Horrace and Rohling, 2016, pg.226).

Contributing to the discussion, assuming that the police officer is a risk-averse person, in conditions of uncertainty – such as during nighttime, when it is raining and with poor visibility – he/she is more likely to use more violence if the police officer believes that doing so will increase his/her security status. In the context that the police officer cannot distinguish the race of the civilian during the encounter, he might behave

[3] The police officer is a risk averse individual, thereby changes in the environment that potentially changes the perception of insecurity by the police officer can impact his/her behavior. A situation in which the police officer perceives more uncertainty or insecurity about the potential outcomes of his/her behavior, he/she might respond with more use of force or more violence that could potentially lead to a fatal encounter.

based on the prior belief that he has about the environment, namely the target population of the racial profiling. If the police officer has a prior belief that black and/or brown people are more prone to violence, on average, the police will commit more homicides in regions where the concentration of black and brown population is larger, and that is evidence of statistical bias discrimination[4]. Furthermore, in a scenario of less uncertainty – during daylight with no rain – and when the police officer has good visibility of the race of the victim, if he/she targets a group of individuals (black and/or brown people), the reason for the racial profiling can be attributable to either SBD (optimal police behavior, if the police officer is in fact targeting a group that is composed of criminals) or RBD (the police officer discriminates even though there is no benefit of doing so).

Our analysis is based on the idea of counterfactual applied to such a discrimination bias discussion. Grogger and Ridgeway (2006) first proposed the concept called "veil of darkness". The assumption is that, during daylight, a police officer has a clearer view of the individual, so they can discriminate based on the color of the individuals' skin, while in the nighttime, it is harder to make the distinction. We incorporated this idea of "veil of darkness" in our study through a regression approach by means of a dummy variable: one (1) indicates homicides committed by police officers during the day, when it is not raining and everywhere in the city; zero (0) stands for homicides committed by police officers during the night, when it is raining and not in avenues (locations that usually have better public lightning). This setting allows us to create a comparison group representing a situation in which there is eventually no racial discrimination.

The empirical strategy consists of a two-level hierarchical model to analyze the impact, on police behavior, of variables related to the race of the victim and variables linked to the environment where the homicide happened. To do so, we used a binary response model in which the decision of the police officer to commit the homicide is linked to the visibility that he/she has about the victim. Adding control variables regarding the characteristics of the individuals is aimed at analyzing solely the effect that the race of an individual has in the police behavior (either RBD or SBD). On the other hand, variables about the population distribution of black and brown people (percentage of either black or brown people in the total population) of the 96 districts of São Paulo are included to identify statistical bias discrimination when the police officer does not have a good visibility of the civilian during the encounter. Control variables at the district level,

[4] Even though the prior belief of the police that black and brown people are more prone to violence, or that they are more likely to be criminals, can be wrong (false belief).

such as poverty, inequality, and urban characteristics are included to obtain efficient estimations. Therefore, the variables of interest are the percentage of the population who is either black or brown in the district population (statistical bias) and the race of the victim (racial bias and statistical bias).

The endogeneity issue is often a concern in the causal inference literature because it could engender a biased estimation. Race of an individual is treated as an exogenous variable by the recent empirical literature analyzing the impact of such variable in police behavior (Coviello and Persico, 2015; West, 2018 Fryer, 2019; Weisburst, 2019; Lieberman, 2020). However, we alleged that the percentage of black and brown people by the total population of the districts might be potentially endogenous. For that reason, we propose the use of Hausman test to check the endogeneity of the percentage of the district's population that is either black or brown, using as an instrumental variable the Euclidean distance between where the homicide occurred and the central district of Sé to test the endogeneity of the racial profile of the district's population. Specifically, we first collected the geocode location where the homicide committed by a police officer occurred, then the Euclidean distance between this location and the polygon centroid of the district of Sé[5] was calculated.

The main obstacle to assess the effects of race on the use of force by the police is the lack of data. Data on lower-level uses of force, such as excessive use of force when arresting civilians, the use of teasers or striking an individual with a baton, which occur much more often than officer-involved shooting, are not available in Brazil. For instance, crime data is compiled at the state level, and only recently some Brazilian states made publicly available data on officer-involved shooting.

Microdata was compiled at the homicide level from the period of January 2013 to February 2021 directly from the police reports for the capital city of São Paulo and its surrounding metropolitan area. We focus our analysis on the State of São Paulo for several reasons. São Paulo is the Brazilian state with the lowest homicide rate, but, in absolute figures, it is the second in police lethality (Cerqueira et al., 2018). Also, the state's Public Safety Office (Secretaria de Segurança Pública de São Paulo in Portuguese) has made available police report data containing the exact location in which the homicide happened. As already detected in the literature, crime often exhibits a spatial pattern (Almeida *et al.*, 2005; Cabral, 2016; Vital, 2018).

[5] The district of Sé is the one where the coordinates of its centroid are closer to the center of the entire polygon of the capital city of São Paulo.

The main contribution of this dissertation to the current literature of police behavior and discrimination is analyzing the problem in the Brazilian context, where the police lethality is larger compared to other developed countries such as the USA and Canada. By means of a hierarchical modeling, we discuss the reasons (RBD and/or SBD) behind the racial profiling in the city of São Paulo. Later, we address several econometric issues, such as measurement errors, omission of relevant variables, and simultaneity, which could lead to biased estimates neglected in previous studies.

This dissertation is structured as follows. Besides this introduction, chapter 2 presents an extensive literature review of racial disparities in police behavior. Chapter 3 introduces the Brazilian context about the racial disparities on crime focusing on its institutional aspects. Chapter 4 discusses the empirical strategy used to address the issue, as well as the data collected. Chapter 5 discusses the results, while section 6 shows some robustness checks. Finally, chapter 6 concludes and points out policy-making implications of this study.

2. THEORETICAL BACKGROUND

This chapter presents the literature review of the economic approach to deal with discrimination, as well as the empirical literature analyzing the effects of race in police behavior. The chapter was divided into three sections: one describing the idea of preference-based discrimination proposed by Becker (1957); another focusing on the early literature of statistical bias discrimination; and, lastly, one with empirical studies of racial discrimination in police activity.

2.1 *Economic approach to racial bias discrimination*

The first economic approach to racial bias was made by Becker (1957), in which the author analyzed the effect of discrimination in the job market. The author proposed a model in which the society is divided in two races, namely, white (W) and black (B), and assuming that members of both groups are perfect substitutes for each other. In the absence of discrimination and nepotism and if the labor market were perfectly competitive, the equilibrium wage rate for white people (W) would equal that for black people (B). Market discrimination against black people exists if discrimination has reduced $B's$ average income by a greater percentage than $W's$. The market discrimination coefficient (MDC) between B and W is defined as:

$$MDC = \frac{Y(W)}{Y(B)} - \frac{Y_o(W)}{Y_0(B)} \tag{2.1}$$

where $Y(B)$ and $Y(W)$ are the actual incomes of B and W, and $Y_0(B)$ and $Y_0(W)$ are their incomes without discrimination. In the absence of racial bias, $MDC = 0$, on the other hand, if $MDC > 0$, there is evidence of RBD. If B is a numerical minority, a necessary and sufficient condition for discrimination against this group is

$$\frac{Y_o(W)}{Y_0(B)} > \frac{l_b}{l_w} \tag{2.2}$$

where l_b and l_w are the labor supplied by the black and white people, respectively. In other words, considering that black people are a minority group, a necessary and sufficient condition for discrimination against this group is that, in the market equilibrium, the average income of white people are larger than the average income of black people, while the number of black workers is smaller than the number of white workers in the market. The author finds abundant evidence of discrimination against non-white people. Another important result is that such discrimination systematically increases with their age and education.

Then, Becker (1957) presents the idea of preference-based discrimination, in which an individual treats another person or another group of individuals belonging to a certain race or ethnicity differently, even though they do not earn any monetary benefit from doing so.

2.2 *Economic approach to statistical bias discrimination*

In contrast with the concept of preference-based discrimination proposed by Becker (1957), Arrow (1973) suggested the idea of statistical discrimination. In a context of uncertainty, in which a person cannot evaluate the characteristics of others, he may treat other individuals differently based on a prior concept that he has towards the group to which the other individuals belong. Such a concept was extended by Phelps (1972) for discrimination in the labor market. If a profit-maximizing employer believes that black employees are less qualified, for example, he will discriminate against this racial group.

Phelps (1972) exemplifies the concept of statistical bias discrimination using as an example the hiring process of a firm that seeks to maximize its profit by selecting the candidate that will bring the more monetary benefits for the firm in the long run. In a recruiting process by a firm, there is a lot of uncertainty about the job applicant. Phelps (1972) argues that if the cost of gathering more information about the job applicant is large, the rational employer (expected utility maximizer) might discriminate against minorities, such as black individuals or women in general, if he believes them to be less qualified for the job.

Becker (1957) and Phelps (1972) discussed, respectively, the ideas of racial bias discrimination and statistical bias discrimination in the labor market, in which the firm or employer wants to maximize its expected profits. However, the core ideas can be extrapolated for the racial discrimination in the police behavior.

The Police Force acts as an entity that wants to maximize the welfare of the population by reducing violence in the society, i.e., the Police offer security by maximizing the arrests of criminals. Note that the Police need to balance between the number of arrests of potential criminals and innocents, given that the trial to decide if the person is convicted of the crime or not often comes later.

The idea proposed by Becker consists of a taste for discrimination, the Police might discriminate against black or brown people just because they are not fond of those individuals. Therefore, a racial-biased police officer might discriminate against a specific individual just because of the color of his/her skin.

On the other hand, statistical bias discrimination arises in the context of uncertainty, in which the police officer is a risk averse[6] individual, who can discriminate based on a prior belief that black or brown people are more likely to be criminals than white individuals. Therefore, if the police officer is a utility-maximizer individual with the goal of reducing violence in society, in a scenario of uncertainty, the police officer discriminates against minorities, if he/she believes that his/her actions will maximize the society's welfare. As argued by Horrace and Rohling (2016), in the absence of any evidence of racial prejudice on the police behavior, the racial disparities on aggregated data could be attributed to optimal police behavior (SBD)[7].

If the police officer has a statistical biased behavior against black and/or brown people, he/she is more likely to have a more intense feeling of insecurity in regions where the probability distribution of the population is more concentrated on black and/or brown individuals, compared to regions where it is more concentrated on whites. Considering that the police officer is a risk-averse individual, his/her feeling of insecurity is a convex function and it is an increasing function in relation to the feeling of uncertainty (if the police officer perceives more uncertainty in the environment, his/her feeling of insecurity is higher).

For example, suppose that a task force composed of only white police officers is working in a region where there is a large concentration of black and/or brown individuals. In a situation where those police officers need to answer an emergency call at night in this region, and they cannot evaluate the situation clearly at their arrival at the scene (high uncertainty), they might act based on previous assumptions about the region (i.e., probability distribution of the race of the population in the region, and crime rate in the region). In other words, when the police officer has a perception of more insecurity and more uncertainty (i.e., nighttime, raining conditions and places with poor public lighting), he/she acts based on a prior belief that he/she has about the environment. If the probability of the police officer committing a homicide is greater on areas where there is

[6] Given the nature of the police job, in which there is a potential risk of life, it is reasonable to assume that the police officer is a risk averse individual.

[7] We are not discussing in this dissertation the idea of false beliefs, for example, the police officer might think that black or brown individuals are more likely to be criminals, when they are not.

a large concentration of black and/or brown people when his/her feeling of insecurity and uncertainty is higher (i.e., nighttime, raining conditions and places with poor public lighting), we interpret that result as evidence of statistical bias discrimination[8].

On the other hand, if the police officer perceives more security and less uncertainty (i.e., during daylight with no rain), and he/she can clearly distinguish the race of the victim, and the probability of committing a homicide in that situation is larger against black and/or brown individuals, we cannot isolate the motivation behind the police officer actions (RBD or SBD), because the civilian can be a criminal or not. If the police officer could assess if the person is a criminal or not and decides to act based on that information, we could assess the motivation behind his/her actions. For example, if the civilian was black or brown and a potential criminal, and the police officer believed that targeting this civilian would increase the societies' welfare by reducing crime, we could interpret as statistical bias behavior. However, if the same individual was not a criminal, and the police officer discriminated him/her, we could interpret as evidence of racial bias discrimination.

In order to identify the reasons for racial profiling, note that we need not only data about the fatal encounters between police and civilian, but data about the non-lethal police-civilian interactions and its outcomes (i.e., the information about the level of compliance between the police officer and the civilian, such as if the civilian reacted or not, or if he was carrying or not illegal drugs and/or firearms).

2.3 *Empirical studies*

Hitherto we described the theoretical foundation behind racial bias and statistical bias discrimination. This subsection presents a literature review of empirical studies. To the best of our knowledge, most of the empirical studies have elaborated the discussion between discrimination and police behavior for the United States of America (Knowles, Persico and Todd, 2001; Grogger and Ridgeway, 2006; Antonovics and Knight, 2009; Coviello and Persico, 2015; Horrace and Rohlin, 2016; West, 2018 Fryer, 2019; Weisburst, 2019; Gonçalves and Mello, 2020; Lieberman, 2020).

This section is further divided into two: one dedicated to empirical studies that follow the approach of hypothesis testing in an equilibrium model proposed by Knowles, Persico and Todd (2001) – hereafter KPT; and other dedicated to empirical studies that

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[8] Assuming that there was no racial prejudice on the police behavior.

opted for the "veil of darkness" approach first proposed by Grogger and Ridgeway (2006).

2.3.1 The Approach KPT for RBD and SBD

Knowles, Persico and Todd (2001) were the first ones to empirically try to isolate the effects of racial bias discrimination and statistical bias discrimination in the data of vehicle searches in the United States. The data set consists of 1,590 motor vehicle searches from the State of Maryland in the United States between January 1995 and January 1999. The summary statistics presented by the authors shows that conditional on being stopped, black motorists are more likely to have their car searched by the police, than white drivers. An explanation for this disparity is racial profiling, in which the race of the driver is one criterion that police officers use to decide whether to search a vehicle or not. KPT proposed a test to isolate RBD and SBD derived from a theoretical model of law enforcement based on the successful rate[9] of searches across drivers' races.

The theoretical model proposed by KPT assumes a continuum of police officers and drivers, and the only race observable is of the motorist[10] denoted by $r \in (B, W)$, where B stands for black and W for white people. Let c denote all the potential variables that the police officer may consider deciding to whether search a car or not (i.e., broken windows, tinted windows, expired license)[11]. Considering the case of c as one-dimensional variable, $F(c|W)$ and $F(c|B)$ are, respectively, the distribution of c in the white and black population.

Conditional on stopping a vehicle, each officer can opt to search motorists of any type (c, r). The goal of the police officer is to maximize societies' welfare by maximizing the total number of successful searches minus a cost of searching cars. Let t_r denote the marginal cost of searching a vehicle driven by a motorist of race r and let us assume that $t_W, t_B \in (0, 1)$. Also, let S denote the event of a successful search.

KPT assumes that the drivers consider the probability of having their car searched when stopped by the police when deciding whether to carry illegal items in the car. If

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[9] A successful search can be defined, for example, if a police driver stops and searches a vehicle and finds illegal drugs or firearms.

[10] KPT did not take into consideration the idea that police officers of the same race as the driver are less likely to discriminate against the latter.

[11] As argued by KPT, due to the lack and poor quality of data, those characteristics are often unobserved or partially observed by the econometrician.

they do not carry, their payoff is zero. If they do carry their payoff is $j(c, r) < 0$ if they are searched, and $v(c, r) > 0$ if not searched.

Let $P(c, r)$ denote the probability that an officer searches a vehicle conditional on stopping the driver with characteristics (c, r). The expected payoff to a motorist from carrying illegal items is:

$$P(c, r)j(c, r) + [1 - P(c, r)]v(c, r) \quad (2.3)$$

Given $P(c, r)$, the driver opts to carry illegal items if 2.3 is greater than zero, on the other hand, if the equation sums to zero, the driver is indifferent between carrying or not illegal items. Let $P(S|c, r)$ denote the probability that a driver of characteristic (c, r) carries contraband[12].

The police officer decides the probability $P(c, r)$ by solving the following equation:

$$max_{P(c,W),P(c,B)} \sum_{r=W,B} \int [P(S|c, r) - t_r]P(c, r)\, f(c, r)dc \quad (2.4)$$

Considering that $P(S|c, r)$ is exogenous, $P(S|c, r) - t_r$ is the expected profit from searching a vehicle driven by a motorist of type (c, r). If $P(S|c, r) - t_r > 0$, then the optimal behavior to the police officer is to stablish $P(c, r) = 1$, in other words, they always search drivers of type (c, r). Additionally, if $P(S|c, r) = t_r$, the police officer optimal strategy is to randomize over whether to search type (c, r).

Knowles, Persico and Todd (2001) define racial bias if $t_B \neq t_W$, and statistical bias if in the equilibrium the police officers have no preference-based discrimination and yet the officer chooses to search a specific race with higher probability, meaning $t_B = t_W$, and $P(c, B) \neq P(c, W)$.

KPT constructs an equilibrium (denoted by an asterisk) in which police officers randomly decide to search drivers, and drivers randomly decide to carry illegal items. For a driver to randomly decide to carry illegal items equation, 2.3 must be equal to zero:

[12] KPT do not allow for the possibility of false accusation by the police officer or planting of evidence by the officer that is conducting the search.

$$P^*(c,r) = \frac{v(c,r)}{v(c,r) - j(c,r)} \tag{2.5}$$

Therefore, equation determines the police officer's search intensity, $P^*(c,r)$. For a police officer to be willing to randomize its searching behavior, $P(S|c,r) = t_r$, for all (c,r).

Suppose that $t_W = t_B = t$, that is, the police officer does not have RBD. Then, for all c, the probabilities of a successful search should be equal across races:

$$P(S|c,W) = P(S|c,B) = t_r \tag{2.6}$$

Notice that this do not imply that in the equilibrium the probability of a police officer searching a black driver should be equal to the probability of searching a white driver, $P^*(c,B) = P^*(c,W)$. The equilibrium search intensity for black drivers may still be higher than for white drivers if:

$$\frac{v(c,W)}{v(c,W) - j(c,W)} < \frac{v(c,B)}{v(c,B) - j(c,B)} \tag{2.7}$$

Translating equation 2.7 into words, the police officer may not have RBD and still searches more vehicles driven by black drivers if the expected payoff for carrying illegal items by black is higher than the expected payoff for carrying contraband by white drivers.

Using the data of vehicle searches of Maryland, KPT then proposes an empirical nonparametric test, the Pearson χ^2, comparing the proportion of successful searches conditional on (c,r) against the null hypothesis of no association between (c,r) and the probability of the driver carrying contraband, $P(S=1|c,r) = P(S=1)$ for all (c,r).

Through the summary statistics of data, Knowles, Persico and Todd (2001) argues that the empirical evidence is consistent with no evidence of preference-based discrimination, given that the rate of successful searches is similar across black, white, and Hispanic people. However, black people are more searched than white people when the characteristics c are not observable, $P^*(B) > P^*(W)$. The authors argues that race may be a proxy for other variables that are unobservable by the police officer and are correlated with both race and crime (i.e., school background, income), leading to SBD.

The empirical results of KPT are derived from the definition of guiltiness of the motorist, which is established based on the amount and type of drugs found in the vehicle search. The authors show that, when comparing only black and white drivers, there is no evidence of SBD.

Anwar and Fang (2006) point to some of the limitations of the KPT equilibrium model. First, the KPT approach assumes that all drivers of a given race have equal probabilities of being guilty (carrying illegal drugs) if searched, regardless of their other characteristics that may be observed by the police. This implies that the drivers' characteristics other than race provide no information about the presence of contraband when the police officer decides to conduct the search, which goes against the police guidelines that require them to base their search decisions on the information that the motorist presents to the officer at the time of the stop. Anwar and Fang (2006) build on the KPT theoretical model by incorporating the hypothesis of non-monolithic behavior of the police[13]. In other words, the model proposed by the authors allows officers of different races to behave differently. So, it allows to test if the search rate of drivers of a particular racial group differs across racial groups of police officers . Under the null hypothesis of the absence of RBD, none of the racial groups of police officers must have a ranking of search rates based on the race of the drivers.

To empirically conduct the test proposed by Anwar and Fang (2006), data about the race of both driver and police officer are necessary. Then, data from the Florida State Highway Patrol from January 2000 to November 2001 consisting of 906,339 stops and 8,976 searches were used. However, the data only contain information about the officer responsible for the stop, and it does not contain information about the police officer responsible for the search. Since the stop and search of a vehicle are made by a troop[14], and the allocation of police officers across troops is not randomly based on their racial group, a resampling method was adopted to define eight troops (one for each Florida County) in which officers of a given race are assigned to different troops with the same probabilities, to assure a baseline comparison group with troops that are not randomly assigned. The empirical test uses a mean t-test to compare the intensity of searches across racial group of drivers between the real troops (not randomly assigned based on the race of the officer) and the randomly assigned troops based on the resampling technique. The

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[13] Anwar and Fang (2006) define police officers as monolithic if they all search a given race of drivers at the same rate.

[14] A troop is defined as a group of police officers.

main results show no evidence of RBD, but Anwar and Fang (2006) argue that it is possible that some troops have racial prejudice because of the low power of the test.

Antonovics and Knight (2009) extended the analysis made by Knowles, Persico and Todd (2001) and Anwar and Fang (2006), developing a new test to distinguish between racial bias or statistical bias. In particular, the assumption incorporated by the authors in their model is that if SBD alone accounts for the racial disparities at which drivers of different racial groups are subject to search, then there should be no difference in the rate at which officers from different racial groups search drivers from any racial group. Using data of traffic stops of Boston for the years of 2001 and 2002, the authors matched information about the driver and the police officer who was responsible for stopping. Antonovics and Knight (2009) found that if the race of the officer differs from the race of the motorist, then the officer is more likely to conduct a search than otherwise. They argue that their results could not be explained by standard models of statistical discrimination and, instead, are consistent with preference-based discrimination.

Fryer (2019) replicated the KPT and Anwar and Fang (2006) tests for discrimination on the data of the Stop and Frisk Program of New York City, as a robustness check for their direct regression approach (more details on section 2.3). Knowles et al. (2001) test for racist preferences by looking at officers' success rate of searches across races. The KPT model assumes that police maximize the number of successful search net of the cost of searching motorists. If racial prejudice exists, then the cost of searching drivers will be different across races. This, in turn, implies that the rate of successful searches will be different across races. Anwar and Fang (2006) built on the KPT approach by affirming that the KPT results may not hold if police officers have a monolithic behavior (as defined previous in this subsection). Anwar and Fang' (2006) statistical test consist of comparing the search rate performed by different racial groups of police officers across different civilians' racial group. If there is a ranking of search rate against a particular group, it can be evidence of racial prejudice against that group.

Fryer (2019) adopted this approach by evaluating whether a civilian was carrying a weapon during the interaction with police. In other words, the authors calculate the probability, for each race, that a suspect had a weapon conditional on being involved in an officer-involved shooting. Given the level of detail in the data from the Stop and Frisk Program, the test was performed for a variety of weapons, including not only small guns but knives or other cutting objects, or assault weapons. Following the insights of Anwar and Fang (2006), Fryer (2019) disaggregates the data by officer race.

Conditional on a police officer using any force during the encounter with the civilian, evidence of RBD arises if no weapons were found when searching minorities, and evidence of SBD arises if firearms were found during the encounter. Using a mean t-test, the results show that black individuals were 1.0% less likely to have a weapon (compared with white ones), conditional on a police officer using any force during the encounter. Hispanics were 0.6% less likely to have a weapon. Both were statistically significant. Therefore, Fryer (2019) interprets this result as evidence of RBD against minorities on nonlethal use of force.

2.3.2 "Veil of darkness" approach

The criminology literature (Horrace and Rohlin, 2016; Terrill, Alpert, Dunham, and Smith, 2003; Withrow, 2004; Zingraff, Smith, and Tomaskovic-Devey, 2000, Grogger and Ridgeway, 2006) discussing racial profiling in traffic stops suggests that a difference between the probability distribution of persons stopped by police and the probability distribution of the population at risk of being stopped is evidence of the existence of racial profiling. As pointed out by Grogger and Ridgeway (2006), this implicit definition reveals the key empirical challenge in testing for racial profiling is defining the risk set, meaning the population at risk of being stopped by the police. Thinking in terms of the idea of counterfactual, the risk set is the comparison group in which we can compare the group of individuals that had their cars stopped by the police.

Knowles, Persico and Todd (2001) contour this challenge by ignoring traffic stop data altogether, focusing on the measures of intensity searches on vehicles conditionally on stopping. The drawback of this assumption is that the KPT model assumes that police officers do not consider the rate at which drivers that are not guilty are being stopped and detained (Grogger and Ridgeway, 2006). Dominitz (2003) shows that the rate at which innocents are wrongly detained is a function of the stop rate, therefore the KPT model omits this information.

Other solution would be to consider the risk set as the resident population where the stop occurred. Grogger and Ridgeway (2006) pointed out a few problems of using this approach. First, perhaps the drivers are not residents in the neighborhood that they are stopped[15]. Second, the population at risk in the surrounding area of the vehicle stop might not represent the characteristics of the drivers. For example, suppose a white individual

[15] This is an issue that we also face in our study, the victim of the homicide by the police can live in a different place than the one that he was killed.

has his car searched for drugs during the night in a neighborhood where the majority of the population is black. In this case, the probabilistic distribution of the population at risk does not represent the probabilistic distribution that the driver belongs. Finally, the behavior of the population at risk might vary from different police exposures.

The alternative approach proposed was based on a simple assumption: during the night, police have more difficult to distinguish the race of the suspect. Then, comparing the racial distribution of stops made during daylight to the racial distribution of stops made at night, it is possible to test for racial profiling. The approach can be summarized by the following equation, as stated by Horrace and Rohlin (2016):

$$\frac{P(S|t,V,B)}{P(S|t,V,\underline{B})} = K(t)\frac{P(S|t,\underline{V},B)}{P(S|t,\underline{V},\underline{B})} \tag{2.8}$$

where S is a binary random variable indicating the event of a police traffic stop at a continuous time t. B is a binary variable indicating if the driver is black, so that $\underline{B}$ indicates that a driver is not black and is at risk. In turn, V and $\underline{V}$ indicate if the driver is visible or not, respectively. $K(t)$ quantifies the discrimination as a function of time, for example, in the absence of profiling, $K(t) = 1$ indicates that the risk of a black driver being stopped is independent of visibility. Hence, $K(t) \neq 1$ captures the extent to which visibility alters the risk of a black driver being stopped; $K(t) > 1$ indicates that in good visibility environment the propensity of black drivers being stopped is greater than that of white drivers.

Because there is no direct measure of the visibility V, Grogger and Ridgeway (2006) use the proxy measure of daylight/darkness. The authors argue that the proxy measure adopted holds if darkness has a race blinding effect on police, and although such a qualitative measure may be less informative than a quantitative one, it is nevertheless an object of considerable importance. The authors also state that the test does not require complete race-blindness in darkness nor complete visibility during daylight/darkness. However, the power of the test increases as the correlation between the proxy measure of daylight/darkness and visibility becomes larger.

Using data of 6,563 car stops in Oakland, California, the authors assessed if the probability of being black conditional on having his/her car stopped and searched is different between daylight and darkness. Results show no evidence of racial discrimination in the police behavior. The authors, however, did not discuss the motivation behind the racial profiling in traffic stops, meaning that they did not try to isolate the statistical bias and racial bias.

Grogger and Ridgeway (2006) point out that one possible feature that can affect the "veil of darkness" idea, and thus generating bias of their hypothesis testing, is the street lightning. Bright street lightning would increase the visibility of the police officer, reducing the difference between the daylight and darkness groups (Horrace and Rohlin, 2016). Extending the approach of "veil of darkness", Horrace and Rohlin (2016) argue that some urban environments are so well lit, in which the visibility at night is the same as during daylight. Using data of Syracuse (NY) between 2006 and 2009, the authors refined the analysis made by Grogger and Ridgeway (2006), taking into account that locations with good street lightning could bias the blindness effect during the dark period. The results showed that the odds of a black driver being stopped when compared to nonblack drivers increase 15% in daylight compared to darkness.

2.3.3 Recent Econometric Studies

As the data availability grew, especially after the Stop and Frisk program, the New York city made its police microdata available, researchers started to opt for a regression approach rather than equilibrium models and hypothesis testing. Anwar and Fang (2006) point out that one of the drawbacks of the KPT approach is the low-power of the test, implying a high probability of a type-II error.

We argue that not only the power of the test is a crucial factor to design an empirical strategy to analyze the relation between discrimination and police behavior but relying on the KPT approach alone is not enough to extract a causal relationship between the two variables. In the modern applied econometrics, often the main goal is to extract a causal link from the data that allows policy makers to design public policies based on the results found. Therefore, recent econometric studies (Coviello and Persico, 2015; Nix, Campbell, Byers, and Alpert, 2017; West, 2018; Fryer, 2019; Knox, Lowe and Mummolo, 2019; Weisburst, 2019; Lieberman, 2020; Gonçalves and Mello, 2020) often opted for a regression approach to find a causal link between racial discrimination and police behavior. This section summarizes the main findings of the recent empirical literature about this topic.

To the best of our knowledge, the recent empirical literature – with some exceptions, i.e., Fryer (2019), Weisburst (2019) and West (2018) – focus only on analyzing the relation of racial discrimination and police behavior, neglecting the discussion of the motivation behind the discrimination, whether RBD and/or SBD.

Coviello and Persico (2015) were the first to analyze the New York Police (NYPD) data on the Stop and Frisk Program, which consists of police officers stopping individuals randomly on the street and questioning them, sometimes searching for weapons, drugs, or smuggling. Using a time span of 10 years, the authors assessed both the decisions of stopping civilians made by the police officers and the allocation of personnel across precincts made by the police chief. The authors employed a linear probability model with the probability of being arrested conditional to being stopped in New York as a dependent variable, with control for year and precinct fixed effects, and they found evidence of racial discrimination in the police approach and suggested further studies on the subject.

Fryer (2019) also investigated whether there is evidence of racial discrimination in the use of the police force using data from the Stop and Frisk Program between the years 2003 and 2013 of New York City. The author also collected information nationwide in the United States for the year 2011 and data from 10 cities across the country to avoid minimizing sampling bias from a single source (i.e., only police departments that know that they do not discriminate grants access to data). Fryer (2019) builds an empirical strategy for the police-civilian interactions that allows for both statistical bias and racial bias discrimination in which police officers are utility maximizers.

The test proposed by Fryer (2019) to identify RBD is based on the relative ranking of use-of-force rates grouped by police officers' race across civilian racial groups. As an example, the author interprets as evidence of RBD if white police officers are more likely to use force on black civilians than black officers, and black officers are more likely to use force on white civilian than white officers. The test to identify SBD is based on the level of compliance between the police officer and the civilian. The argument used by the author is that, if police officers are purely statistical discriminators, then during the police-civilian interactions, if the civilians' signal to police regarding their likelihood of compliance becomes increasingly deterministic (i.e., encounters where the police officer reported that the civilian was compliant on every measured dimension), racial differences should disappear. Through logit regressions, the author concludes that black and Hispanic individuals are more than 50% likely to experience some form of police violence with the use of non-lethal weapons compared to other races, even when the level of compliance is the same. Therefore, Fryer (2019) interpreted this result as evidence of RBD. In the case of police actions using lethal weapons (firearms), the author does not find evidence of either racial bias discrimination or statistical bias discrimination on the part of the police forces.

Knox, Lowe and Mummolo (2019) argue that the estimates made by Fryer (2019) understate the causal effect of racial bias by not considering racial differences in police-civilian interactions prior to the encounter, such as patrolling habits and the decision of whether to stop an individual.

Weisburst (2019) builds on the work of Fryer (2019) using data from the Dallas Police Department in Texas about arrests, officers and non-shooting use of force. Analyzing more than 130,000 arrests between 2013 and 2016, the author finds out that black civilians are disproportionately likely to be involved in an incident containing any level of force, stemming from differences in likelihood of arrest. Conditional on arrest, use-of-force rates do not differ systematically by civilian race. Further, Weisburst (2019) found out limited evidence of taste-based racial bias in use of force, conditional on arrest. This work extends the investigation in Fryer (2019) by leveraging information on officer race in non-shooting use-of-force incidents and by examining relationships between racial disparities in use-of-force incidents and arrests. As noted by Fryer, these conclusions could be related to the self-selection of Dallas as a case study, as this department's willingness to release use-of-force data may be a function of lower levels of bias.

West (2018) assesses racial bias in automobile crash investigations using data on 440,000 crash investigations conducted by a single State Police Department (SPD) during 2006-2012 in the United States. With respect to car accidents, the police encounters are demonstrably exogenous with respect to drivers' race. The support for this empirical identification is straightforward: unlike a traffic stop, police officers are dispatched to crash investigations. The specific driver to be investigated is determined by the occurrence of the automobile crash, in advance and independently of any officer involvement, based mostly on proximity between the nearest patrol and the accident scene. Adopting a differences-in-differences methodology, West (2018) found evidence that State Police officers imposed significantly more traffic citations to drivers whose race differs from their own. This bias is evident for both moving and nonmoving violations, the latter indicating a preference for discriminatory leniency towards same-race individuals. The treatment is invariant to socioeconomic factors. The police officers cite other-race drivers more frequently regardless of their age, gender, vehicle value, or characteristics of the local community.

West (2018) attributes his findings to a preference-based discrimination (Becker, 1957) rather than a statistical discrimination (Arrow, 1973). Since the author is exploring data from car crashes, the official objective of the investigation is to determine the factors that lead to the collision rather than maximizing a "hit rate" for finding contraband (minimizing the utility of statistical discrimination). Moreover, West (2018) argues that citations for nonmoving violations, such as expired vehicle registration, cannot be consistent with only statistical discrimination. The author concludes that his results offer ample support to the evidence of racial bias but cannot fully rule out statistical discrimination. Despite discussing the mechanism behind the racial profiling found in the results, West (2018) did not try to design an empirical strategy that tries to isolate both biases.

Nix, Campbell, Byers, and Alpert (2017) analyzed 990 police fatal shootings using data compiled by *The Washington Post* in 2015. The authors examined if there was evidence of implicit bias by using multivariate regression models that predict whether the civilian was not attacking the police officer or other civilian just before being fatally shot and whether the civilian was unarmed when fatally shot. Considering that the victims were not attacking the police officer, the results pointed out that civilians from minority groups whose race differs from the police officer on duty were statistically significantly more likely to be fatally shot than white individuals. Regarding unarmed individuals, black civilians were more than twice as likely to be killed by the police officer than a white victim. One of the contributions of Nix, Campbell, Byers, and Alpert (2017) is the use of data at the national level addressing the possible sampling bias that could be present in other similar studies that address the problem in smaller areas. It is possible, for example, that only police stations that do not have a history of racial profiling are the ones providing the data about the police actions.

Ross (2015) also analyzed Police Shootings in the United States to investigate the extent of racial bias in the shooting of civilians by police officers between 2011 and 2014. The author employed a spatial multi-level Bayesian model to assess the ratio of the probability of being armed versus unarmed, by race. In other words, the dependent variable of the model is assumed to have a binomial distribution, for example, equal one if the individual was black, unarmed and shot by the police, and zero, if the individual was white, unarmed and shot by the Police. The first level of the model is composed of only the dependent variable, and the second level is the county-level that includes information about the population size, percentage of blacks among the population, income, Gini index, and searches on Google about racism. The main results showed that probability of being black, unarmed and shot by the police is around 3.5 times the probability of being white, unarmed and shot by the Police. Another interesting finding that is in line with our main results is that the relative risk ratio of being shot by the police is larger in counties where there is a sizable portion of black residents.

Lieberman (2020) analyzed data of New Jersey from 2012 to 2016 at the incident level to identify racial disparities in police use of force. The author employed a logit model and found that black individuals and Hispanics are more likely to have more severe types of force used against them, if some force was used by the Police. In order to check for department-specific racial differences, Lieberman employed empirical Bayes methods and found statistically significant variations across police departments in the State. The results showed that a larger racial diversity in a police department is not correlated with the racial disparities, and poorer areas with greater economic inequalities have a larger racial disparity. This result motivated a robustness check of our main results by incorporating a fixed effect term of Police Stations in our empirical strategy (further details in chapter 6).

Gonçalves and Mello (2020) used data of speed tickets from the Florida Highway Patrol to analyze racial discrimination against minorities by individual police officers. The authors used the cutoff point of the speed limit to create comparison groups based on the leniency of the police officer. The main contribution of the study was to assess the racial discrimination from the police officer perspective, isolating the effect of individual police officers on racial discrimination. The authors find that 40% of the task force is responsible for all the racial disparities in the data.

Outside of the United States, the empirical literature assessing the effect of race on police behavior is scarce. Wortley and Owusu-Bempah (2009) conducted a survey using telephone interviews between October 2006 and January 2007 with 1,522 residents of Toronto, Ontario. The goal of the survey was to explore the perception that immigrants and racial minorities had about the Canadian Criminal Justice System, including the Police. The results showed that black respondents had a perception of being discriminate by the police.

From an empirical standpoint, there are two major flaws in the previous works about studying racial bias in police behavior. To the best of our knowledge, the majority of the studies neglect important variables related to the environment in which the incident occurred, such as the proportion of black and brown people by the total population in the surroundings, enabling to see if the police behavior changes in locations with high black density population due to a statistical discrimination bias.[16] Besides, these studies neglect the possibility of spatial autocorrelation due to the spatial displacement of crime.

A lot of debate in the literature about economic disparity discusses the ideas of statistical bias discrimination and racial bias discrimination. However, on the empirical side of the literature, there is no clear identification strategy to distinguish between the two effects. We have joined the discussion by building on the “veil of darkness” assumption of Grogger and Ridgeway (2006) in a causal manner. We argue that during the “dark” period, the police officer cannot distinguish the race of the civilian and he behaves based on a prior belief that he has about the location. Also, during the “dark” period, the police officer is likely to have a larger perception of risk and insecurity, increasing the probability of behaving in a way that minimizes his/her risk. Hence, contributing to the literature, we propose a spatial multilevel model, in which we argue that RBD and SBD can arise at the individual level (during the “light” period), and the SBD can arise at the aggregated level, namely the districts of São Paulo (during the “dark” period).

Concluding, Table 1 below exhibits the summary of the cited works here.

[16] Despite including detailed information about the location where the homicide happened, the empirical strategy adopted by Ross (2015) lacks a structure to capture the causal relationship between race and police behavior. The goal of the study was to predict the relative risk ratio across different races and armed status in police shootings in the USA.

Table 1- Characteristics of the studies of racial bias in police activity

Authors	Region	Period	Empirical Strategy	Dependent variable	Independent variables	Conclusions
Knowles, Persico and Todd (2001)	Maryland - USA	January 1995 to January 1999	Equilibrium model / hypothesis testing	Police officer search in traffic stops.	Race of the driver, gender of the driver, drugs (if any were found and the type), characteristics of the vehicle (old, luxury and ownership), paraphernalia and night	The probability of being found with any quantity of drugs are equal across races. For larger quantities, black people are more likely to carry them.
Anwar and Fang (2006)	Florida - USA	January 2000 to November 2001	Equilibrium model / hypothesis testing	Police officer search in traffic stops.	Race of the police officer, race of the driver, drugs (if any were found and the type), characteristics of the vehicle (old, luxury and ownership), paraphernalia, time-of-day, neighborhood	No evidence of RBD or SBD. The authors suggested, however, that it is possible that some of the Troops have racial prejudice due the low power of the test.
Grogger and Ridgeway (2006)	Oakland - USA	June 15 to December 30, 2003	Equilibrium model / hypothesis testing	Police officer search in traffic stops.	Race of the driver, gender of the driver, drugs (if any were found and the type), characteristics of the vehicle (old, luxury and ownership), paraphernalia, time-of-day, neighborhood	The authors found no evidence of racial profiling. Data on a full set of post stop outcomes are needed to provide a comprehensive assessment of racial profiling. The empirical results apply only to Oakland and say nothing about the presence or absence of racial profiling in other jurisdictions.
Antonovics and Knight (2009)	Boston - USA	April 2001 to April 2003	Equilibrium model / hypothesis testing	Police officer search in traffic stops.	Race of the police officer, race of the driver, gender of the driver, drugs (if any were found and the type), characteristics of the vehicle (old, luxury and ownership), paraphernalia, time-of-day, neighborhood	Police officers are more likely to do a search in the vehicle if the race of the officer differs from the race of the driver.
Wortley and Owusu-Bempah (2009)	Toronto-Canada	October 2006 to January 2007	Population survey	Perception of discrimination	Age, gender, immigration status and race of the responder	Perceptions of racial bias are particularly widespread among black respondents

Table 1- Characteristics of the studies of racial bias in police activity

(continued)

Authors	Region	Period	Empirical Strategy	Dependent variable	Independent variables	Conclusions
Coviello and Persico (2015)	New York - USA	2003 to 2012	OLS	Arrests	Race of the individual, time fixed effect, precinct fixed effect, crime fixed effect	White pedestrians are slightly less likely than black pedestrians to be arrested conditional on being stopped.
Horrace and Rohlin (2016)	Syracuse - USA	2006 to 2009	Equilibrium model	Police officer search in traffic stops.	Race of the driver, gender of the driver, drugs (if any were found and the type), characteristics of the vehicle (old, luxury and ownership), paraphernalia, night, Streetlights, time spline, high black population indicator, high crime indicator, CENSUS tract indicator	Controlling for streetlights there is evidence of racial profiling.
West (2018)	Non-identified Police Department in USA	2006 to 2012	Differences-in-differences	Citations in automobile crashes	Race of the driver and the officer, gender, age, light condition, controls regarding the accident, time fixed effects, vehicle age and luxury	State Police officers issue significantly more traffic citations to drivers whose race differs from their own.
Fryer (2019)	New York and other 10 cities in the USA	2003 a 2013	Logit	Use of force	Gender, a quadratic in age, civilian behavior, whether the stop was indoors, whether the stop took place during the daytime, whether the stop took place in a high-crime area, during a high-crime time, or in a high-crime area at a high-crime time, whether the officer was in uniform, civilian ID type, whether others were stopped during the interaction, missing indicators in all variables, precinct, and year fixed effects.	On non-lethal uses of force, black people and Hispanics are more than 50 percent more likely to experience some form of force in interactions with police. On the most extreme use of force – officer involved in shootings - no racial differences were found either in the raw data or when contextual factors are taken into account.

Table 1- Characteristics of the studies of racial bias in police activity

(continued)

Authors	Region	Period	Empirical Strategy	Dependent variable	Independent variables	Conclusions
Ross (2015)	United States	2011 to 2014	Multi-level spatial Bayesian model	Armed status and race	Population size, portion of the population that is black, median income, Gini index, and number of searches of "racism" on Google	Unarmed blacks are 3.5 times more likely to be shot by the police compare to unarmed whites. The relative risk of being shot by the police is higher in counties with a sizable portion of black residents.
Weisburst (2019)	Dallas - USA	2013 to 2016	OLS	Use of force	Arrestee's age and gender; Officer age, gender, trainee status, and a quadratic in years of experience; 3) Proportions of violent, property, drug crime, disorderly conduct, prostitution, and traffic offenses; police beats and eight half-year fixed effects.	Conditional on arrest, use-of-force rates do not systematically vary across civilian race, and there is limited evidence of taste-based bias among officers.
Gonçalves and Mello (2020)	Florida - USA	2005 to 2015	Differences-in-differences	Car stops	Race, age, gender, Florida license, prior stops and prisons, Log zip code income, vehicle price and age, location, and time fixed effects	40% of the Police task force are responsible for all the racial disparity in the data.
Lieberman (2020)	New Jersey - USA	2012 to 2016	Logit and Empirical Bayes	Use of force	Race of individual, time, type of incident, officer rank, subject behaviors, subject sex, a quadratic of the subject's age, department fixed effects.	Black people and Hispanics are more likely to have more severe types of force used against them conditional on force. There is significant variation across police departments.

3. INSTITUTIONAL BACKGROUND

This section is aimed at presenting the institutional background about the police apparatus of the state of São Paulo, composed of two forces, namely, the Civil Police and the Military Police.

One of the aspects of a criminal justice system involves designing public safety policies to fight crime. In the Brazilian institutional framework, it turns out that public safety constitutionally hinges on police forces under authority of the states[17] by means of Civil Police, which are responsible for criminal investigation, and Military Police, which are, in turn, responsible for ostensible, preventive and repressive policing. (Vital, 2018).

The Brazilian Constitution (chapter III, article 144) enacted in 1988 basically establishes six different law enforcement agencies:

(i) Federal Police;

(ii) Federal Highway Police;

(iii) Federal Railway Police;

(iv) Civil Police;

(v) Military Police and Military Firefighters;

(vi) Federal, State and District Criminal Police (Constitutional Amendment n. 104, 2019).

Since the focus of this study is to analyze the behavior in ostensible policing, we will focus on the state's police forces, that is, the Military Police and the Civil Police of the State of São Paulo (MP).

It was possible to obtain important data from The Military Police of São Paulo by means of the Access to Information Law (Federal Law n. 12.527, 2011)[18]. In 2019, there were 82,869 Military Police officers for the entire State of São Paulo. Of the total, 64% of those officers declare themselves as white individuals and only 34.6% of the police officers (29,675 total) declare themselves as black or brown people.

Data from the Foundation State System of Data Analysis (Seade in Portuguese) shows that the Paulista population[19] shows that the racial profile of the State is similar to the MP, namely, 63.9% of the state population are white, 29.1% are brown, 5.5% are black, 1.4% is yellow, and 0.1% is Native-American.

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[17] Brazil is divided into 26 states and 1 federal district (see figure A1 in the appendix).

[18] This law was enacted on November 18, 2011. The Access to Information Law enacted the constitutional right regarding information of the Public Institutions.

[19] Those individuals who are born in the State of São Paulo.

However, data collected from the police reports available by the Public Safety Institution of São Paulo (SSP/SP in Portuguese initials) reveal a quite different picture in the racial profile of homicides by the police. In 2018, 821 individuals were killed by the police, of whom 485 were black or brown (almost 64%), 276 were white, and 60 were not identified.

Recent events, such as the social movement Black Lives Matter and the series of riots around the world preceded by the death of George Floyd in the United States, raise the discussion of police lethality in social sciences. The cases of police violence, although few, feed a feeling of unsafety that makes it difficult to control and can even contribute to the escalation of other forms of violence (Mesquita Neto, 1999).

A key difference between a civilian and a police officer is that the latter is allowed by law to use force against another individual in order to fulfill his/her constitutional duties. Mesquita Neto (1999) points out four different concepts to define police violence. First, from the legal point of view, police violence is defined as the situation in which the police officer uses force illegally, i.e., when the officer uses excessive force (such as torture) in operations. This is a rigid concept of police violence, which leads to the second point of view, in which a police action can be legal but immoral, i.e., when an officer uses more force than necessary for the situation. This last concept is based on the legitimacy use of force. Third, there is the concept that Mesquita Neto (1999) names as journalistic. For example, police actions that can be legal and legitimate but are not well received by the public opinion. Lastly, as defined by Klockars (1995): "*excessive use of force should be defined as the use of more force than a highly skilled officer would find necessary to use in that particular situation.*" Mesquita Neto (1999) emphasizes that this last definition of police violence should be used for being more professional and suggests the need for police professionalization and the improvement of police training and professional development before suggesting the need for punishment of police officers involved in acts of violence to control police violence.

Data from a victimization survey from the PNAD (Pesquisa Nacional por Amostra de Domicílios in Portuguese) in 2009 shows that about 4.5% of the Brazilian population suffered from some type of physical aggression made by police officers in the previous year, representing 1.4 million people in absolute terms. Taking into account the race of the individual, 6.5% percent of the black population claimed that they had suffered some form of aggression, in contrast with 3.7% of the white people. From the total, 33.1%

claimed that they did not go to the police department to report the occurrence because they were afraid of retaliation.

The most extreme use of force that a police officer can exercise is shooting and killing. That being said, we are focusing our attention on this type of violence in our analysis, especially because in Brazil, as far as we know, there is no data available regarding non-lethal police-civilian interactions.

4. EMPIRICAL STRATEGY

This chapter is dedicated to present the empirical strategy as well as detailed information about the dataset used in this study.

The core idea of this dissertation is to stablish a causal link between discrimination and police behavior. Being more specific, we address if the race of the victim of homicides by police officers in São Paulo is a driving factor in the decision of the officer to commit or not the homicide. Besides, we also contribute to the literature by assessing whether the probability distribution of racial groups in the districts' population of São Paulo is a characteristic that police officers rely on to decide whether to commit homicide in a context of relative risk when he/she cannot distinguish the race of the victim.

This chapter is divided into two sections: one dedicated to the empirical strategy adopted to identify if there is evidence of RBD and/or SBD in the police behavior in São Paulo; and other devoted to present the data collected from homicides committed by the police in São Paulo.

4.1 Identification strategy

Our empirical strategy is built on the "veil of darkness" assumption of Grogger and Ridgeway (2006) in a binary response model. We developed on the idea of the authors that during nighttime, the police officer does not have a great visibility of the civilian, and therefore he/she cannot distinguish the race of the individual. We also take into consideration that some places in the cities are so well illuminated that could compromise the assumption (Horrace and Rohlin, 2016). We take a step further, and we take into consideration if it was raining during the police-civilian encounter, arguing that during raining periods the visibility deteriorates.

Hence, the sample of homicides committed by the police in São Paulo is divided in two comparison groups based on the visibility[20] that the officer potentially had during the encounter. One considers the homicides committed by police officers during daylight[21], in days with no rain and anywhere in the city. The other is composed of homicides committed by the police during nighttime, in rainy days, and in locations with poor street illumination. This division allows us to isolate the racial component of police

[20] Since visibility is not directly observed, we use proxies based on the work of Grogger and Ridgeway (2006) and Horrace and Rohlin (2016) to define a measure of visibility.

[21] To avoid compromising the homogeneity of the groups due to changes in luminosity by the end of the daylight (5 pm to 7 pm) and during twilight (5 am to 6 am), we defined as nighttime the period between 7 pm and 5 am, and daytime otherwise.

officer due to the visibility effect. During periods of good visibility, the police officer can better distinguish the race of the individual who he is about to shoot, while at night he cannot. Besides, we excluded the homicides that took place in avenues of the analysis. This is because there is better public lighting in those streets[22], so the police officer can distinguish better the race of the victim. By defining those two groups, we indirectly incorporate a measure of relative risk in the model, in the sense that it is reasonable to assume that the risk-averse police officer perceives more risk during nighttime, in places with poor public lighting (not in avenues) and raining, compared to the daylight when it is not raining.

Our empirical strategy, therefore, relies on the qualitative measure of visibility that we adopted. The ideal scenario is darkness, raining and poor public lighting has a blinding effect on the police officer regarding the race of the civilian. But this is an ideal scenario that may not be true, and the lack of data makes it impossible to test this hypothesis. However, we argue that even if the proxy of visibility proposed leads to a measurement error, on average, the visibility during the night, when it is raining and not in avenues is much lower than the visibility during the day when it is not raining. Therefore, if there is any measurement error in consequence of the qualitative measure of visibility used, it will be small, and on average our estimated effects would still be valid.

The empirical model consists of a two-level spatial hierarchical approach based on a linear probability model at the first level, in the sense that we are estimating the probability of being killed by the police based on the visibility that he/she has about the civilian during the encounter, as a function of race and other variables that could alter the police behavior (if the police officer responsible for the homicide was working when the incident happened, temperature[23], wind[24], and if the homicide happened in a slum or in a remote area)[25]. If the race of the victim has no statistical significance in the regression, this is evidence of absence of discrimination (Grogger and Ridgeway, 2006). The second level of the hierarchical model is composed of variables related to the São Paulo district's

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[22] Following the critic of Horrace and Rohlin (2016) about Grogger and Ridgeway (2006) work.

[23] There is a growing literature in the effects of temperature on human behavior (Anderson et al., 2000; Cohn, 1990; Field, 1992; Vital and Almeida, 2020). Higher temperatures are linked to more activity that often are associated to more crime.

[24] The hypothesis for including wind is to allow for the possibility that maybe the police officer was aiming at shooting not to kill the person but in days with strong winds and in great distances, there is a chance that the bullet deviates and the homicide happened. Therefore, we opted for including this confounding variable.

[25] It is possible to get more granular data about the victim from the police reports, such as age and profession. However, as argued in the next section of this chapter, the number of missing values in these variables are large. Therefore, including them in the empirical strategy could potentially harm the estimates due to sample bias.

characteristics[26], in which our interest lies on the percentage of district's population that is either black or brown, but also includes variables that previous literature showed to have a link with the propensity to criminal activity (Fajnzylber *et al.*, 2002; Kelly, 2000).

Let y_{ij} be a dummy variable equal to one (1) if the homicide committed by the police happened during the day with no rain and anywhere in the city and equals zero (0) if the homicide was committed by a police officer during nighttime in rainy days and in locations with poor luminosity (anywhere in the city, except in avenues). Note that i stands for the individual, while j consists of the 96 districts of São Paulo.

Its first level is expressed as being a linear probability model:

$$y_{ij} = \beta_{0j} + \beta_1 black\_brown_i + \alpha X_i' + u_{ij} \tag{4.1}$$

where X_i' is the matrix of covariates included to improve the efficiency of the estimated coefficients of the model.

On equation 4.1, our interest relies on the β_1 coefficient, meaning that the race of the individual is an important driving factor for the police officer to commit a homicide, i.e., if this coefficient is positive and statistically significant at conventional levels, there is evidence of either racial and/or statistical bias in police behavior. The recent economic literature (Coviello and Persico, 2015; Fryer, 2019; Lieberman, 2020; Weisburst, 2019) in racial disparities assumes that the race of the individual is exogenous, and we think that it is a valid identification assumption.

The second level of the hierarchical model is as follows:

$$\beta_{0j} = \alpha_{00} + \beta_2 prop\_black\_brown_j + \pi Z_j' + u_j \tag{4.2}$$

The second level is attributed to the characteristics of the 96 districts of São Paulo, our variable of interest is the percentage of black and brown individuals by the total population of the district ($prop\_black\_brown_j$), which allows us to identify the presence or not of statistical bias discrimination.

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26 As argued by Ross (2015), a spatial multi-level models allow us to assess a relative risk ratio across the spatial units. And we extended the previous analysis made by the author by assessing the causal link of the portion of the São Paulo district's population that is either black or brown. Our hypothesis is that the statistical bias in police behavior can arise when the police officer discriminates more in districts with a sizable black and/or brown population.

The matrix Z_j' is composed of variables at the district level such as homicide rate, afforestation in the streets, inequality and poverty variables. The α_{00} is the grand mean of the model.

Combining equations 4.1 and 4.2 into a single equation result in the multilevel model:

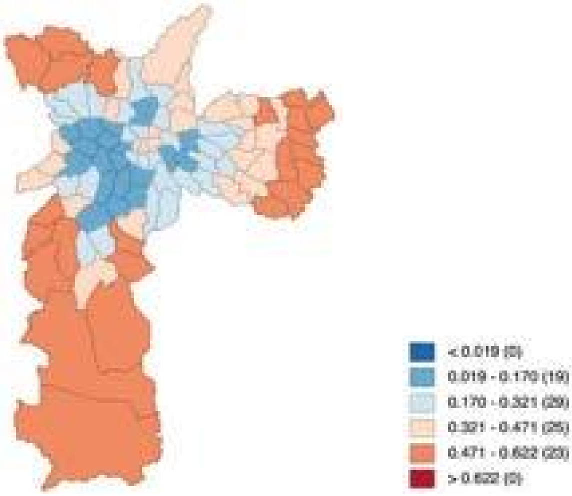
$$y_{ij} = \alpha_{00} + \beta_1 black\_brown_i + \beta_2 prop\_black\_brown_j + \alpha X_i' + \pi Z_j' + \left(u_j + u_{ij}\right) \tag{4.3}$$

Our identification assumption about police behavior is that at the individual level (first level) both statistical bias (Arrow, 1973) or preference-based bias (Becker, 1957) can arise from the coefficient of the race of civilian that was killed by a police officer (β_1). While at the district level (second level), only statistical bias discrimination can arise from the coefficient of the racial profile of the district's population (β_2).

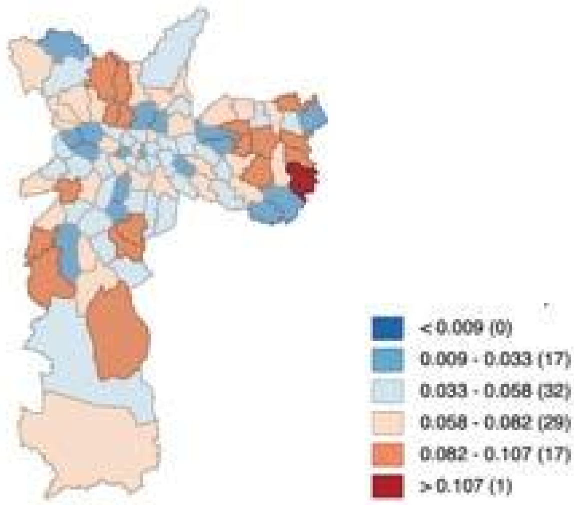
Including the variable of proportion of the population who is black or brown at the district in the models can engender endogeneity issues. Firstly, the endogeneity can arise from omitted unobservable characteristics of the black and brown population that can be included in the error term, and it is correlated with the district's racial probability distribution.

Secondly, the endogeneity can be due to reverse causality. It is common in Brazil that criminal organizations linked to drug traffics rule some areas of the cities, and it is usually the suburban neighbors where the proportion of black and brown people is higher. If the Police act with more violence in these areas, the members of the criminal organization could react with more violence as well, determining simultaneously these two variables.

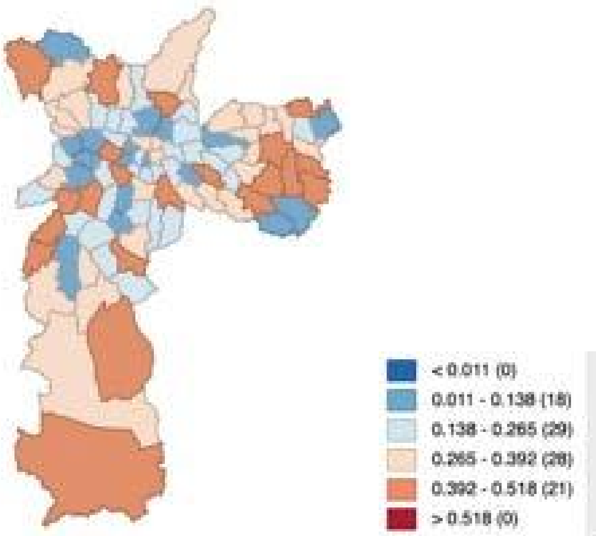
We propose the use of an external instrumental variable, namely the distance between where the police officer committed the homicide and the district of Sé in the central part of the city. The idea behind the use of this instrument is that the neighborhoods with the highest concentration of black and brown individuals are in the periphery of São Paulo, which is farther away from the central part of the city, as it can be seen in Figure 3. With the rise of technology and the accessibility of recording devices, such as mobile phones or surveillance cameras, it is easy for most part of the population to record violent actions committed by police officers. A recent example is the recording video of George Floyd on May 2020 in Minneapolis, while an older example is the recording video of Rodney King on March 1991 in Los Angeles. The possibility of being recorded acts as homogenizing effect throughout the territory.



a. $\frac{Tota\ brown\ population_j}{Total\ population_j}$



b. $\frac{Total\ black\ population_j}{Total\ population_j}$



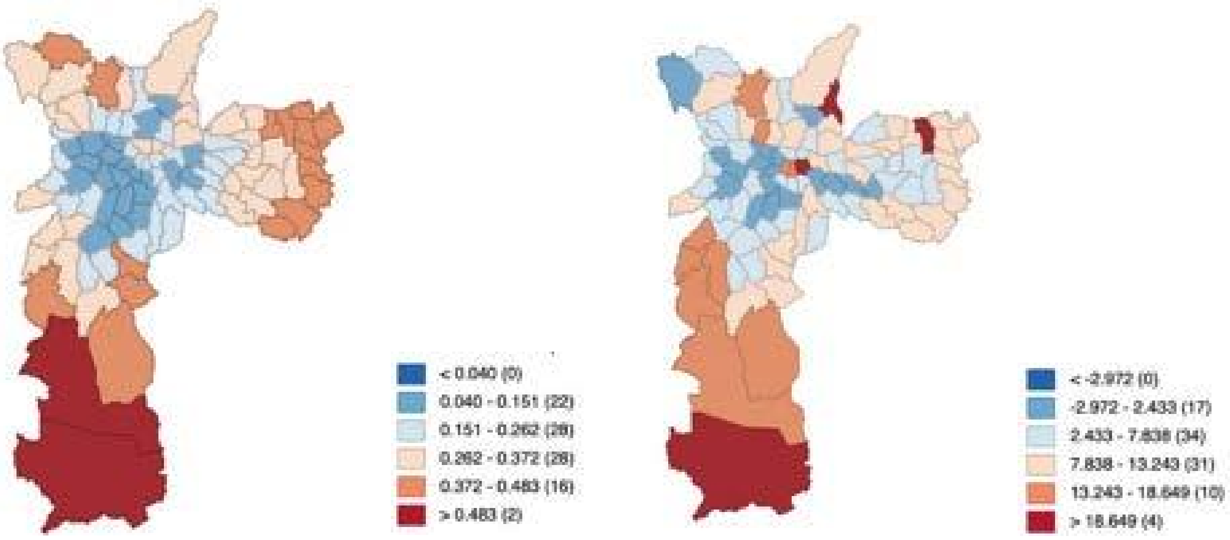
c. $\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$

Figure 3: Standard deviation maps of the racial distributions across districts

Source: prepared by the authors using data from the 2010 IBGE Census.

As the time goes by, technology is becoming more available to the population of low-income families. Nowadays, almost everyone, even in suburban areas, has access to a cellphone with a camera that can record a police action. Therefore, we argue that the police behavior does not change from the center of the city to the suburban areas because the police officer can be recorded by anyone using mobile phones or surveillance cameras. Figure 4 displays: a) the distribution of poverty across the districts of the city of

São Paulo; and b) the distribution of homicide rate across the districts of the city of São Paulo.



a. Poverty b. Homicide rate in 2016

Figure 4: Standard deviation maps of poverty and the 2016 homicide rate

Source: prepared by the authors using data from the 2010 IBGE Census and SSP/SP.

4.2 Data

The main contribution of this dissertation is to discuss police behavior and discrimination in Brazil, where the police lethality is higher than in the USA, where the literature has been focusing on (Knowles, Persico and Todd, 2001; Grogger and Ridgeway, 2006; Antonovics and Knight, 2009; Coviello and Persico, 2015; Horrace and Rohlin, 2016; West, 2018 Fryer, 2019; Weisburst, 2019; Gonçalves and Mello, 2020; Lieberman, 2020). In doing so, we had to adopt an empirical strategy that allowed us to identify if there is any form of bias (RBD and/or SBD) in police behavior based on the data available in Brazil.

Unlike the data available in the United States, such as the data from the Stop and Frisk Program of New York City, or data about stop and search of vehicles, in Brazil we do not have a source of public data about non-fatal police-civilian interactions. Therefore, the KPT approach that relies on having an outcome of an unsuccessful event (i.e., searching a vehicle and not finding illegal drugs[27]) is not feasible due to lack of data for the Brazilian case.

[27] Since the available data in Brazil only consists of homicides, we also do not have any measure of "intensity" of the approach, i.e., excessive use of force. Consequently, an approach such as the one proposed by Fryer (2019) is also not feasible.

The data used for this dissertation are police reports stemming from the Public Security Office[28] (SSP in Portuguese initials). These police reports stand for a rich micro dataset about homicides committed by police officers at the individual level for the period of January 1, 2013, to February 28, 2021, for the State of São Paulo. This microdata includes the description of the victim. in addition to the location in which the event took place. Unfortunately, we do not have information about the police officer responsible for the homicide. However, we have information about the police station where the police officer responsible for the homicide registered the crime[29].

Following substantial data cleaning[30], the total number of observations is 1,196[31] homicides committed by the Police in the city between 2013 to 2021. Out of the total of those, 52.1% were committed by police officers during daylight, with no precipitation in the city of São Paulo. Figure 5 depicts the data cleaning. Table 2 presents some descriptive statistics of the variables at the first level, while Table 3 presents the same information for the variables at the second level of the hierarchical model.

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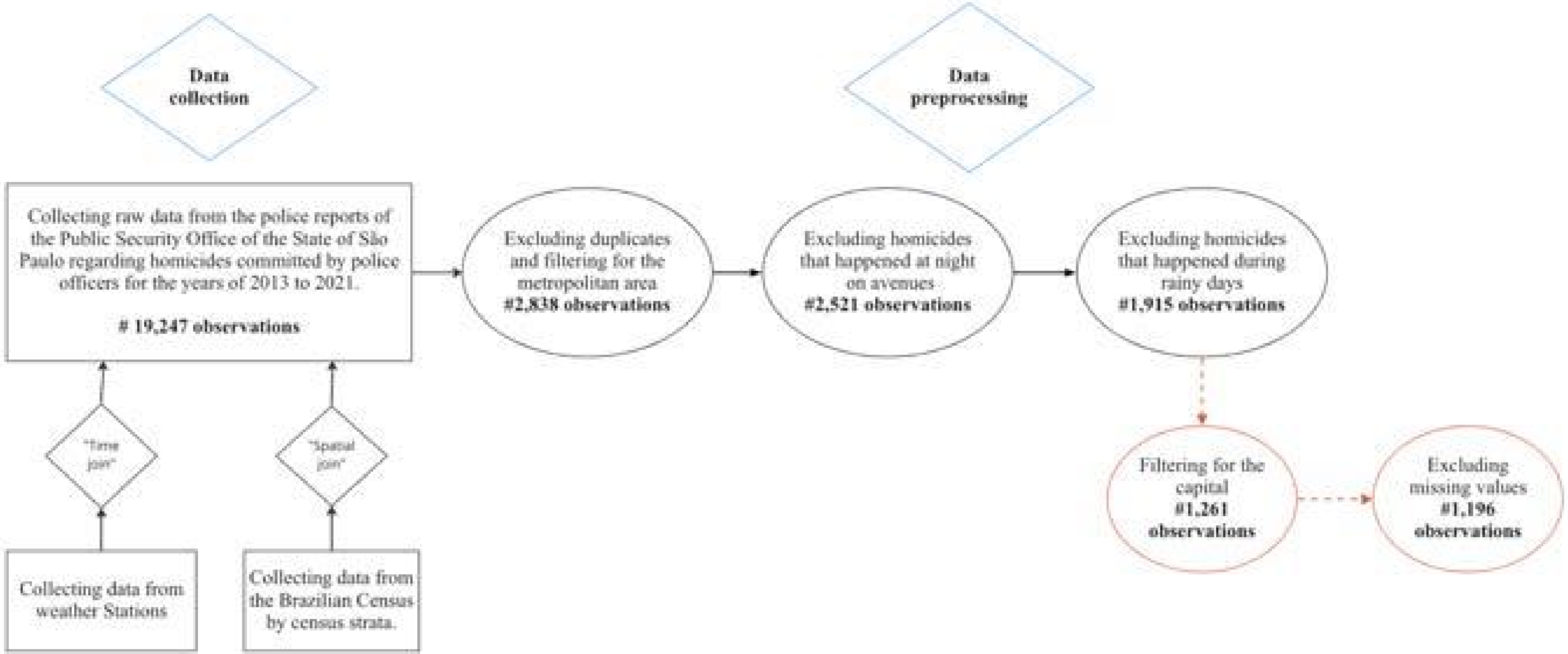
[28] http://www.ssp.sp.gov.br/transparenciassp/Consulta.aspx

[29] As argued in Chapter 3, the probability distribution of the race of the population and the probability distribution of the race of the police is similar. Assuming that police officers are randomly assigned to police stations, as a robustness check (Chapter 6), we included police station fixed effects to evaluate if there is any change in the main results.

[30] We collected data from weather stations that have measurements every six hours, therefore we use the information about the date and time in which the homicide happened to define the weather conditions during the event. The Brazilian census data on the other hand was merged into the original dataset using the geolocation of the homicide and the centroid of the polygon of the census strata. Later, we aggregate the data about the census tracts by São Paulo districts, using the proximity between the centroids of both polygons. Since, São Paulo has 18,952 census strata areas and only 96 districts, the overlap between neighboring regions does not cause a large measurement error.

[31] Out of the 1,261 observations from the São Paulo capital city, 65 of those did not include information about the location of the crime. Since we employed robust standard errors clustered by districts, we exclude those of the data.

Figure 5: Preprocessing steps of the data cleaning



Source: prepared by the authors.

Table 2: Descriptive statistics of the variables at the first level (RBD and/or SBD)

Variable	Description	Source	Mean	Std. Dev.	Max.	Min.	Number of missing values
Homicide committed by police officers (dependent variable)	Dummy variable equals one if the homicide was committed by a police officer during daylight with no rain, and zero if it was committed during nighttime, in rainy days, and anywhere in the city except in avenues.	Public Safety Office of São Paulo	0.521	0.500	1.000	0.000	0
Black and brown	Dummy variable equals one if the victim was black or brown, and zero otherwise.	Public Safety Office of São Paulo	0.680	0.466	1.000	0.000	0
Black	Dummy variable equals one if the victim was black, and zero otherwise.	Public Safety Office of São Paulo	0.109	0.311	1.000	0.000	0
Brown	Dummy variable equals one if the victim was brown, and zero otherwise.	Public Safety Office of São Paulo	0.572	0.495	1.000	0.000	0
Not working	Dummy variable equals one if the police officer was not working when the incident happened, and zero otherwise.	Public Safety Office of São Paulo	0.266	0.442	1.000	0.000	0
Slum	Dummy equals one if the event happened in a slum or in a remote area, and zero otherwise.	Public Safety Office of São Paulo	0.026	0.157	1.000	0.000	0
Temperature	Mean temperature throughout the day.	National Institute of Spatial Research	20.772	3.283	28.429	9.009	6
Wind	Mean wind throughout the day.	National Institute of Spatial Research	1.914	0.642	4.317	0.517	6

Note: prepared by the authors

Table 3: Descriptive statistics of the variables at the second level (SBD)

Variable	Description	Source	Mean	Std. Dev.	Max.	Min.	Number of missing values
Homicide rate	Number of homicides committed by civilians by the total population of the district multiplied by 100,000	Public Safety Office of São Paulo and Brazilian CENSUS 2010	10.577	16.590	77.349	0.000	58
Poverty	Proportion of the number of households that has a total income of less than two Brazilian minimum wages by the total number of families in the district	Brazilian CENSUS 2010	0.282	0.185	0.491	0.088	58
Inequality	Proportion of the number of households that has a total income of less than two Brazilian minimum wages by the number of families with total income superior to 40 minimum wages	Brazilian CENSUS 2010	58.431	618.456	3152.80	0.257	58
Green area	Percentage of the houses in the district with trees in the streets.	Brazilian CENSUS 2010	0.674	0.131	0.986	0.319	58
Proportion of black and brown people	Proportion of black or brown population in the district divided by the total district population	Brazilian CENSUS 2010	0.393	0.151	0.601	0.058	
Proportion of black people	Proportion of black population in the district divided by the total district population	Brazilian CENSUS 2010	0.169	0.202	0.152	0.051	58
Proportion of brown people	Proportion of brown population in the district divided by the total district population	Brazilian CENSUS 2010	0.311	0.167	0.551	0.063	58

Note: prepared by the authors.

We rely on information about two different levels in a hierarchical structure: the first level regarding the individual and the second level with variables with characteristics of the districts of São Paulo. On the first level, we have information about the race of the victim of homicide committed by police, a dummy variable indicating if the police officer was working during the time, a dummy variable if the homicide happened in a slum or in a remote area, and the average wind and temperature throughout the day.

One of the variables that is present in the police reports is the age of the victim. However, the information is not always included in the police reports. For instance, from the full sample compiled for the empirical strategy proposed of 1,261 observations, 354 observations did not include the age of the civilian (almost one quarter of the total sample). The missing information about the age of the victim could be due to an unobserved idiosyncratic factor that can result in sample selection bias. Therefore, including this variable in the empirical strategy could potentially engender a sample selection bias.

Weather is one variable that is mostly neglected in behavioral theories of crime (Vital and Almeida, 2020). The impact of temperature in human behavior has been a subject of interest of researchers for a long time (Anderson, et. al, 2000; Cohn, 1990; Field, 1992; Stec and Klabjan, 2018). Findings reveal that higher temperatures lead to more activities, and more criminality (Michel et al., 2016). Recently, Vital and Almeida (2020) assessed the impact of precipitation in the homicide rate in the city of Rio de Janeiro. Their findings reveal that there is a negative correlation between precipitation and crime.

Our hypothesis about the inclusion of variables linked to weather is that they can have a significant impact on the behavior of the police officer. If higher temperatures can have an impact on crime, it may have an impact on the prior beliefs of the police, which may lead to the decision to shoot or not someone. We also argue that police officer is not an easy job. Despite all the training, a lot of factors can have an impact on the crime scene. For example, in a day with strong winds, the police officer may try to shoot someone not in a fatal way, but due to a long distance and the high winds, this shot turns to be fatal for the victim. This hypothesis justifies the presence of the variable of wind in the multilevel equation. The National Institute of Spatial Research (INPE) is the source of the weather data, which has a daily frequency.

The variables of interest at the second level (Table 3) are the proportion of the district's population that is either black or brown. We will work with three different specifications of this variable: one with the joint proportion of black or brown people, one with only black individuals, and one with only brown individuals. However, Brazil is a country where the diversity of races is quite large, and the definition of being of a specific race is based on self-declaration, including the one collected by the Brazilian Institute of Geography and Statistics (IBGE). An individual may have a skin whiter than others, and still consider himself black due to social history and background. The self-declaration of race could lead to measurement error of how the police officer sees the racial profile of the districts. For example, if a district has a small population of self-declared black individuals that have darker skins, and declare themselves brown people, this could lead to a different view of how the police officer sees the total racial profile of the district. For this reason, we argue that the model that considers the proportion of the black and brown population in the total population of the district is more suited to analyze the prior belief that police officer has, conditional to the racial profile of the district.

Considering the second level of the hierarchical model – namely, district-level – the variables inserted in the models are the ones that could have an impact on the decision of the police officer to kill someone and could reflect characteristics of the place that the incident occurred (Table 3). The sociodemographic data was collected from the Brazilian Census made by IBGE[32].

The sociodemographic conditions of the districts can influence how the police officers behave in these neighborhoods. It is often covered by the news, police actions with more violence than required happening in in poor areas of the city rather than in their richer counterparts. The poverty variable is defined as the number of households that have a total income of less two Brazilian minimum wages by the total number of households in the district. Using information based on the minimum wage is better in the sense that it is corrected by the inflation every year. Consequently, the variable does not need to be corrected due to heterogeneity of inflation across the districts. Inequality has the same reason to be present in the models. Regions with higher inequality are usually linked to more criminality (Fajnzylber and Araujo Jr, 2001) and since the police officer is a risk averse agent, locations where the crime rate is higher, the police officer may have more violent reactions.

[32] IBGE is the Brazilian official agency that provides statistical information for government.

The police behavior can be influenced by the level of criminality of the surrounding districts. Areas with more criminal records can demand more violence in police actions. Homicide rate is the proxy for criminality in our models, due to the low underreporting of this type of crime. As mentioned before, spatial autocorrelation due to displacement of crime is a common issue when dealing with crime in Brazil (Almeida et al., 2005; Cabral, 2016; Vital, 2018). We included a spatially lagged variable of homicide rate in the models to address this problem that could lead to bias estimations due to the omission of relevant variables.

The urban demographics literature has a consensus that cities with more green areas are linked to better quality of life (Coder, 2011; Lohr, Pearson-Mims, Tarnai, and Dillman, 2004; Sheets and Manzer, 1991). The number of trees in the streets is therefore a proxy for the quality of life in the urban area. The same idea is valid for the access of public lighting by the families.

Table 4 presents the summary statistics of race groups aggregated based on the proxy of visibility. The numbers show, for example, that black and brow people correspond to 69.1% of the homicides committed by police during periods of good visibility, against 67% in periods of poor visibility.

Table 4: Summary statistics grouped by visibility

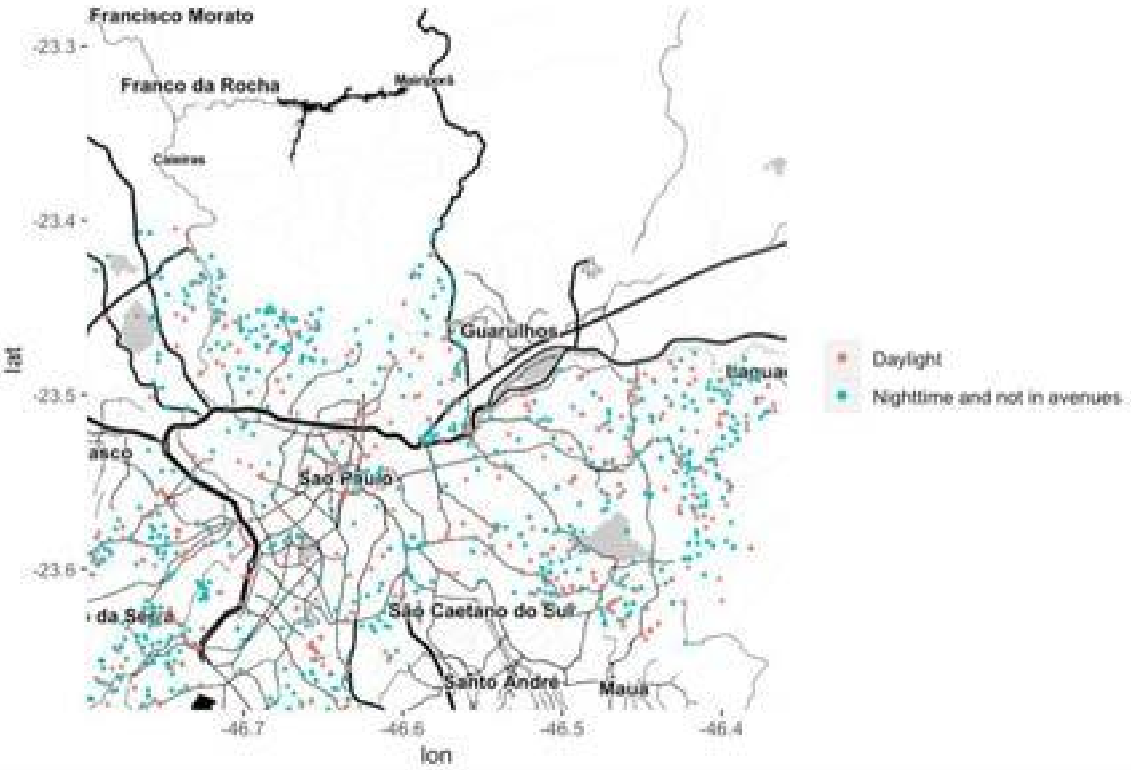
	Daylight with no rain			Nighttime, with rain, and not in avenues		
First level (racial bias and/or statistical bias)						
	Black	Brown	Black and brown	Black	Brown	Black and brown
Mean	0.121	0570	0.691	0.097	0.573	0.670
Standard deviation	0.323	0.495	0.462	0.296	0.495	0470
Coefficient of variation (%)	239.673	86.842	47.00	304.883	86.400	70.200
Second level (statistical bias)						
$\frac{Total\ \{\}\ population_j}{Total\ population_j}$	{Black}	{Brown}	{Black and brown}	{Black}	{Brown}	{Black and brown}
Mean	0.069	0.316	0.383	0.070	0.333	0.404
Standard deviation	0.229	0.118	0.137	0.021	0.107	0.124
Coefficient of variation (%)	34.312	37.370	35.919	29.646	32.225	30.839
n		603			658	

Note: prepared by the authors.

The first columns of Table 4 present the fraction of individuals killed by police officers grouped by racial group divided between “light/dark”. One possible concern is that if the data collected have enough variability across different race groups. As we can see by the coefficient of variation, there is a large dispersion of the distribution of all six variables of interest across the two comparison groups. Among civilians killed during daylight with no rain, 12.1% were black and 69.1% were either black or brown; among the civilian victims of homicide committed by police officers during nighttime, with rain and not in avenues, 9.7% were black and 67.0% were either black or brown. If anything, this comparison suggests “reverse” racial profiling, because it shows that non-black civilians are disproportionately killed by police officers during the period with visibility (Grogger and Ridgeway, 2006).

Figure 6 shows a plot of the occurrences for the city. The dots represent homicides that happened in police actions. The red dots are the homicides that occurred during daylight, with no rain, whereas the blue ones represent homicides committed by police officers in the dark time, in rainy days and not in avenues of the metropolitan area of the city.

Figure 6: Spatial distribution of homicides in the metropolitan area of São Paulo



Source: Data from the Public Safety Office of São Paulo

The data generating process is a spatial point process,[33] in which we tested for spatial autocorrelation (clustering) in the dependent variable using G-function, K-function and L-function. We rejected the null hypothesis that the spatial point process comes from a completely spatial random (CSR) process, concluding that we do not have a homogeneous Poisson process (HPP). See more technical details about these results in appendix A.3.

[33] See technical details about spatial point processes in appendix A.2.

5. RESULTS

In this chapter, we present the results regarding the endogeneity issue of the variable of percentage of the population of the São Paulo districts that is black or brown and the results of the hierarchical model. The chapter is therefore divided in two sections, one for each topic.

5.1 Formal Checks for Endogeneity[34]

The coefficients estimated by ordinary least squares (OLS) could be biased since the variable of interest at the second level, namely, the percentage of the district's population that is either black or brown, could be correlated with the error term of the regression. Let equation 5.1 below be the linear causal model of the combined hierarchical model of equation 4.3. The goal is to estimate both the causal effect of the race of the victim ($black\_brown_i$) and the causal effect of the probability distribution of the race of the district's population ($prop\_black\_brown_j$) in the decision of the police officer to commit a homicide during daylight (y_{ij}). The data generating process of y_{ij} is, therefore, a function of $black\_brown_i$ and $prop\_black\_brown_j$:

$$\begin{aligned} y_{ij} &\equiv f(black\_brown_i, prop\_black\_brown_j) \\ &= \beta_{0j} + \beta_1 black\_brown_i + \beta_2 prop\_black\_brown_j + M_{ij} \end{aligned} \tag{5.1}$$

where y_{ij} is defined as before ($y_{ij} = 1$ if the homicide committed by the Police happened during the day with no rain and anywhere in the city, and $y_{ij} = 0$ if the homicide was committed by a police officer during nighttime in rainy days and except in avenues)[35]; and M_{ij} is made of all the other factors that is part of the data generating process, including a vector of control variables at both individual and district level, and fixed effects, defined as follows:

$$M_{ij} = \alpha X_i' + \pi Z_j' + \gamma_{PS} + \varepsilon_j = C_i'\gamma + \varepsilon_j \tag{5.2}$$

The notation remains the same as defined in the previous chapter: X_i' is the transpose matrix of covariates at the first level; Z_j' is the transpose matrix of covariates at

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[34] This section is based on the discussion of chapter 4 about instrumental variables of Angrist and Pischke (2008).

[35] Note that *i* stands for the individual, while *j* refers to the 96 districts of São Paulo.

the second level; γ_{PS} is a police station fixed effect[36]; ε_j is the error terms clustered by districts, and it is the random part of the potential outcome y_{ij} left over after controlling for the variables C_i'. Combining equations 5.1 and 5.2, we get the following:

$$y_{ij} = \beta_0 + \beta_1 black\_brown_i + \beta_2 prop\_black\_brown_j + C_i'\gamma + \varepsilon_j \qquad (5.3)$$

The exogeneity assumption of the linear causal model states that:

$$E(black\_brown_i\ \varepsilon_j) = 0 \qquad (5.4)$$

$$E(prop\_black\_brown_j\ \varepsilon_j) = 0 \qquad (5.5)$$

By way of explanation, the error term is uncorrelated with $black\_brown_i$ and $prop\_black\_brown_j$ by assumption. If this assumption is correct, then OLS estimations of the parameters in equation 5.3 are unbiased estimations of the true model parameters. However, if this assumption does not hold, for instance, when the percentage of the district's population that is either black or brown ($prop\_black\_brown_j$) is correlated with ε_j, it results on biased estimates. Therefore, we say that in this case $prop\_black\_brown_j$ is an endogenous regressor if the expectation of the error term (ε_j) conditional on the racial profile of the district's population is different from zero (violation of equation 5.5)[37].

The endogeneity could also arise, for example, due to simultaneity bias of the dependent variable and the independent variable. In the city of São Paulo, districts with a larger percentage of black and brown population are usually the districts that concentrate more criminal activity. Imagine the following scenario: a police officer is supposed to answer an emergency call in a district in periphery of the capital, where the percentage of black and brown people in the population is larger. The risk averse police officer is more prone to act truculently and violently because he/she regards this situation as riskier. On

[36] In equation 4.3, 00 captures the fixed effect of the districts. In equation 5.1, we included, instead, a police station fixed effect. It is reasonable to assume that the location of the police stations did not vary much during the period analyzed, since it takes time to build new facilities. However, as argued in the next chapter, the police station can be thought of as a control for "bad apples" (Lieberman, 2020), and we test this assumption as a robustness check for the main result.

[37] As far as we know, the current literature of discrimination bias in police behavior assumes that equation 5.4 always holds, that is, the race of victim is assumed to be exogenous (Coviello and Persico, 2015; West, 2018 Fryer, 2019; Weisburst, 2019; Lieberman, 2020).

the other hand, the criminals may respond to the police actions with more violence in retaliation of the police actions. This may lead to reverse causality between the racial probability distribution ($prop\_black\_brown_j$) of the districts and police behavior, which consequently can engender the endogeneity of the latter in the naïve ordinary least estimates of equation 5.1. Historically, black and brown people are the stratum of the population that were more neglected by the State in previous decades, which lead them to be marginalized to peripherical regions of the city and often resorting to criminal activity. Since it is not the one of the goals of this dissertation to analyze the historical link between poverty, race, and crime, we will not attempt to discuss any further.

Econometricians have long made use of instrumental variables to consistently estimate parameters when ordinary least squares fail to do so in the presence of endogenous regressors. Instrumental variable estimation is possible when we have at least one variable, Q_i, that is not correlated with the clustered error term, ε_j, it is highly correlated with the endogenous regressor, and it is not an independent variable in the original equation 5.1 (Murray, 2006; Wooldridge, 2010). This assumption is called exclusion restriction since the instrumental variable, Q_i, can be said to be excluded from the causal model of interest, equation 5.1.

Therefore, an instrumental variable to be considered needs to meet two key assumptions (Cunningham, 2021; Glymour, Pearl, and Jewell, 2016; Pearl, 2009):

(i) Relevance: $Cov\left(\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}, Q_i\right) \neq 0$;

(ii) Validity (exclusion restriction): $Cov(Q_i, \varepsilon_j) = 0$.

When both conditions are valid, we can state that we have an identification strategy that is able to find unbiased estimations of the true model parameters using 2SLS estimators.

Given the exclusion restriction, it follows from equation 5.3 that:

$$\beta_2 = \frac{Cov(y_{ij}, Q_i)}{Cov\left(\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}, Q_i\right)} \tag{5.6}$$

An instrumental variable is said to be weak when it explains little of the variation of the endogenous variable (fail of the relevance assumption) or it is somehow correlated with unobserved factors presented in the error term (fail of the validity assumption). Hausman, Stock, and Yogo (2005) argues that weak instruments have two implications: bias in the estimated 2SLS coefficients, and hypothesis tests of the estimated parameters may suffer from severe size distortions.

To test the hypothesis of endogeneity of the proportion of black and brown people in the district's population, we propose a Hausman test based on a two-stage least squares estimation using as an external instrument the distance between the location where the homicide committed by a police officer took place and the district of Sé ($Q_i = distance\_se_{ij}$), in the central part of the capital[38]. Figure 7 depicts an example of the distance between a homicide committed by the police and the district of Sé.

Figure 7: Example of the Euclidean distance between the district of Sé in the central part of the city and a homicide committed by a police officer in the Anhanguera district (Northwest side of the capital)

Source: prepared by the author.

[38] The measurement of distance adopted by us is the absolute Euclidean distance between the two coordinates, namely, the location where the homicide happened and the centroid of the polygon of the district of Sé (-23.5489, -46.6388). Therefore, the measurement results in the difference of degrees between the two geographical coordinates.

The idea behind using the Euclidean distance between a district in the central part of the city and the location where the homicide happened consists of the intrinsically exogeneity of geographic distance. With the advance of technology, more people have access to recording devices such cellphone cameras and surveillance cameras, in the sense that nowadays, even in the peripheric region of the city, the population can record police actions. This fact could lead to a more homogeneous police behavior throughout São Paulo's area. If a police officer intends to commit a homicide, he will do so despite being in the central part of the city or in the suburbs. In the late 1970's or 1980's, this instrument would probably be invalid because there were probably no recording devices in the peripherical areas.

The Hausman test to check for the endogeneity of the race probability distribution of the districts is based on a two-stage least square (2SLS) estimation, and it can be summarized as follow:

(i) The first level of the Hausman test is summarized by equation 5.7:

$$prop\_black\_brown_j = \theta_0 + \theta_1 distance\_se_{ij} + \theta_2 black\_brown_i + \rho X_i' + \kappa Z_j' + \varphi_t + \gamma_j + \nu_j \quad (5.7)$$

The reduced form of $prop\_black\_brown_j$ is regressed on all the exogenous variables in equation 5.1 plus the instrumental variable $distance\_se_{ij}$.

(ii) The fitted values using ordinary least squares of the residuals in equation 5.7, $\widehat{\upsilon_j}$, are included as an independent variable at the second stage of the two-stage least squares:

$$y_{ij} = \alpha_0 + \alpha_1 black\_brown_i + \alpha_2 prop\_black\_brown_j + \alpha_3 \widehat{\upsilon_j} + \zeta X_i' + \tau Z_j' + \varphi_t + \gamma_{PS} + \vartheta_j \quad (5.8)$$

(iii) If the estimated coefficient $\widehat{\alpha_3}$ is not statistically significantly different from zero, we reject the null hypothesis of endogeneity of $prop\_black\_brown_j$

Table 5 presents the results of the first stage equation, 5.7, estimated by OLS.

Table 5: Hausman test based on the first stage estimated equation

Dependent variable: $\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	Estimated coefficient	t-test
$Black\ and\ brown_i$	-4.13e-4 (0.002)	-0.231
$Not\ working_i$	-0.004 (0.003)	-0.922
$Slum_i$	-0.002 (0.006)	-0.301
$Wind_i$	0.003* (0.001)	1.751
$Temperature_i$	-5.50e-5 (4.17e-4)	-0.109
$Poverty_j$	0.290*** (0.062)	4.096
$Inequality_j$	-5.28-5 (4.93e-5)	-0.639
$Green\ area_j$	-0.415*** (0.059)	-7.008
$Homicide\ rate_j$	-5.02e-4 (5.12e-4)	-0.892
$Spatial\ lagged\ homicide\ rate_j$	-9.37e-4 (0.002)	-0.570
$Distance\ Sé_{ij}$	0.986*** (0.271)	3.640
Intercept	0.472*** (0.091)	2.378
Year fixed effect	Yes	
Police Station fixed effect	Yes	
n	1,196	
R^2	0.951	
Partial R^2	0.146	
$F - statistic$	188.90***	
Minimum eigenvalue statistic	188.90	
Shea's partial R^2	0.146	
Shea's partial adjusted R^2	0.060	

Source: Prepared by the authors.
Note: standard errors in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10.
Year fixed effects and Police Station fixed effect are present in the model. The spatially lagged homicide rate is constructed using a spatial weights matrix of the five nearest neighboring districts.

By performing the Hausman test to check for the endogeneity of the percentage of the district's population that is either black or brown as described in the three above, using as an external instrumental variable the distance to the location where the homicide happened and the district of Sé ($Q_i = distance\_se_{ij}$), we do not reject the null hypothesis of exogeneity ($p - value = 0.186$ associated with the α_3 coefficient in equation 5.8 at the second-stage).

Stock, Wright, and Yogo (2002) suggest as a rule of thumb to decide whether the instrument is weak or not. If the t-value of the estimated coefficient of the instrumental variable at the first stage regression is less than 3.3, we have evidence that the instrumental variable is a weak predictor of the endogenous variable. In this case, the second stage estimated standard errors will be large and the 2SLS estimates will tend to be biased towards the corresponding OLS estimates. We found a t-value equal to 3.640 for the estimated coefficient θ_1 at the first stage equation 5.2. More recent literature (Hull, Kolesár, and Walters, 2022) also shows that the rule of thumb of the first-stage t-statistic proposed by Stock, Wright, and Yogo (2002) is conservative for the just-identified case, and it is possible to find strong instruments below this threshold with an increase of variance (larger standard errors and small bias).

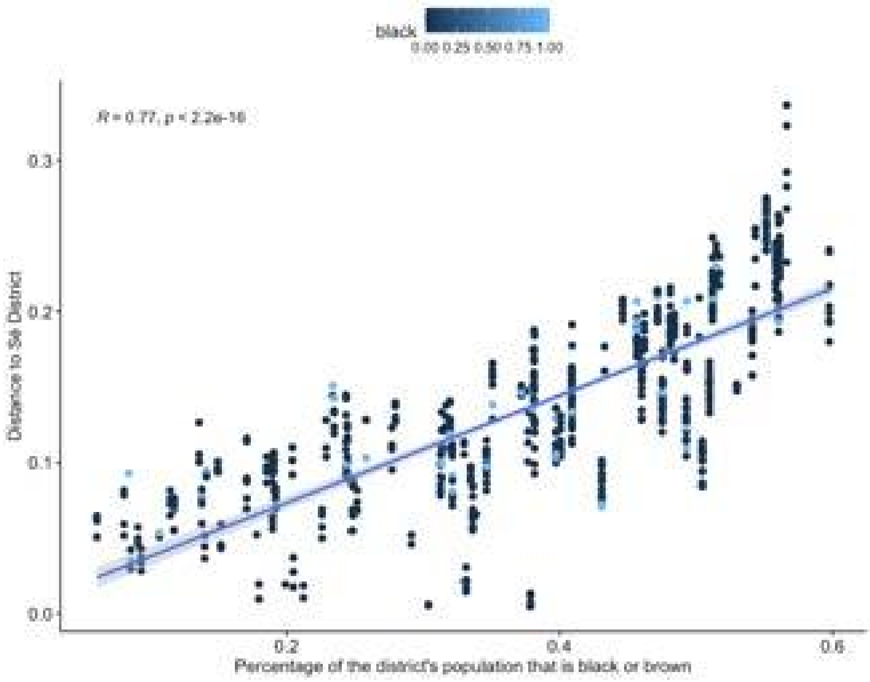
Looking at more usual statistics, the $R^2 = 0.951$ and the $F - statistic = 188.90$ at the first-stage regression provides initial evidence that the instrumental variable adopted is valid. The partial $R^2 = 0.146$ is calculated by eliminating the effects of all other covariates at the first-stage equation. Therefore, it informs how much of the variance of the percentage of the district's population that is either black or brown is explained only by the instrumental variable. Since we have a just identified IV, Shea's partial R^2 is equal to the partial R^2.

The relevance assumption states that a good instrumental variable needs to be highly correlated with the endogenous regressor and not correlated with the error term.

$$Cov\left(\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}, Distance\ Sé_{ij}\right) \neq 0 \tag{5.9}$$

If the relevance assumption does not hold, the denominator in the equation 5.6 will be biased for a small value than the true parameter, causing the β_2 in the original causal model to be biased for a larger value than the true model parameter. The Pearson correlation between the potential endogenous variable the percentage of the district's population that is either black or brown and the instrumental variable used, the distance to the location of the homicide to the district of Sé is 0.77 (Figure 8). Hence, it seems that using the distance between the location where the homicide happened, and the centroid of the district of Sé meets the relevance assumption.

Figure 8: Pearson correlation between the potential endogenous variable, percentage of black and brown individuals in the total district's population, and the instrumental variable, distance to the location where the homicide happened and the centroid of the district of Sé.



Source: prepared by the authors.

The validity assumption, also called the exclusion restriction assumption (Angrist and Pischke, 2008). However, it cannot be directly tested since ε_j is not observed and we have the case of just identified IV. Cunningham (2021) argues that the validity assumption can be assessed if we are not able to find a theoretical explanation for the direct impact of the instrumental variable on the outcome variable that is not via the impact of the instrumented variable. For example, if we explicitly state that black and brown civilians are more likely to be killed by police officers during daylight as far as they are further away of the district of Sé, there is no logical causal link between the two events that is not connected with the fact that districts further away from the district of Sé have larger concentrations of black and brown residents.

Another evidence that the instrumental variable used is not weak is the minimum eigenvalue statistic proposed by Cragg and Donald (1993), that is exactly equal to the F-statistic found at the first-stage equation. For finite samples, if the first-stage F-statistic is greater than the minimum eigenvalue statistic, there is evidence of weak instruments, which is not the case. In sum, we have evidence that the proportion of black and brown individuals out of the total district's population does not suffer from endogenous issues.

5.2 Hierarchical modeling

In this section, we present the results of the effect of race on police behavior, using the spatial hierarchical model described in chapter 4 with the data of the city of São Paulo for the period from January 2013 to February 2021.

Since the null hypothesis of exogeneity of the proportion of the district's population that is black or brown was not rejected by the Hausman test, the hierarchical model was estimated using restricted maximum likelihood (REML). Therefore, the combined hierarchical model is the one presented by equation 4.3:

$$y_{ij} = \alpha_{00} + \beta_1 black\_brown_i + \beta_2 prop\_black\_brown_j + \alpha X_i' + \pi Z_j' + (u_j + u_{ij}) \qquad (4.3)$$

The first level is composed of the individual characteristics (race) and variables linked to the event (temperature, wind, if the police officer was working at the time, and if the homicide happened in a remote area or in a slum). The second level is made up of the variables of the district of São Paulo where the homicide happened, such as the proportion of black and brown people in the total population of the district, the proportion of trees in the streets by the total area, homicide rate, poverty, inequality, and a spatially lagged homicide rate to take account for spatial displacement of crime[39]. Table 6 presents the results for the estimations.[40]

[39] Using the procedures proposed by Baumont (2009) and the procedure of Stakhovych and Bijmolt (2009), a spatial weights matrix of the five nearest neighbors was adopted to construct the spatially lagged homicide rate in the districts.

[40] The need for including the variables of the second level was tested using an ANOVA procedure. As we can see by the statistically significance of the χ^2 statistics, the more suited model is the one that includes all the variables present in Table 6.

Table 6: Results of the Hierarchical models

	Model 1	Model 2	Model 3
	First level (racial bias and/or statistical bias)		
$Black\ and\ brown_i$	-0.004 (0.031)	.	.
$Black_i$		-0.062 (0.052)	.
$Brown_i$	.	.	0.010 (0.032)
$Not\ working_i$	0.054 (0.034)	0.048 (0.054)	-0.048 (0.036)
$Slum_i$	0.021 (0.097)	0.088 (0.128)	0.103 (0.108)
$Wind_i$	-0.107 (0.087)	-0.015 (0.137)	-0.133 (0.092)
$Temperature_i$	-0.118 (0.087)	-0.044 (0.133)	-0.094 (0.092)
	Second level (statistical bias)		
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	-0.196*** (0.076)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	-2.374** (1.187)	.
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	-0.437** (0.171)
$Poverty_j$	0.042 (0.086)	-0.086 (0.122)	0.051 (0.088)
$Inequality_j$	0.044 (0.124)	0.354* (0.185)	-0.008 (0.125)
$Green\ area_j$	-0.044 (0.100)	-0.001 (0.131)	-0.039 (0.105)
$Homicide\ rate_j$	0.059 (0.075)	0.073 (0.110)	0.022 (0.076)
$Spatially\ lagged\ homicide\ rate_j$	0.128* (0.071)	0.287*** (0.100)	0.132* (0.073)
	Random effect		
Variance u_j	0.002	0.000	0.002
Variance ε_{ij}	0.245	0.246	0.245
	Fixed effect		
Intercept α_{00}	0.757*** (0.135)	0.639*** (0.188)	0.759*** (0.145)
Year fixed effect	Yes	Yes	Yes
Log Likelihood	-852.03	-355.2	-757.11
AIC	1746.0	756.1	556.2
χ^2	11.409*	15.618**	11.584*
N	1,196	508	1,066
Number of groups		96	

Source: Prepared by the authors.

Notes: standard error in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10.

The dot indicates that the variable is not included in the model. Year fixed effects are present in all six models. The spatially lagged homicide rate is constructed using a spatial weight matrix of the five nearest neighboring districts.

We used three different specifications of the hierarchical models depending on the race of the victim:

(i) Specification 1: includes only the dummy variable of being black or brown as the explanatory variable of interest, and the proportion of brown and black people as the total population of the district.

(ii) Specification 2: the explanatory variable of interest is now a dummy variable equal to one if the victim was black and zero otherwise, and at the second level, we focus on the proportion of black population in the total population of the district.

(iii) Specification 3: focus the attention on only brown individuals, so the explanatory variable of interest in this model is a dummy if the victim was brown and zero otherwise. At the second level, we included only the total brown population divided by the total population of the district.

The number of observations varies across the three models since we eliminate the other races in the baseline estimations of models 2 and 3. For example, the sample of model 2 does not contain black individuals, while model 3 does not contain black individuals.

As argued in the empirical strategy chapter, Brazil has a large diversity of races and the definition of being of a specific race is based on self-declaration, which could lead to measurement error of how the police officer sees the racial profile of the districts. Also, the social literature often considers black and brown people in the same group. Therefore, we argue that model 1 the more suited model regarding the statistical bias.

As stated in previous chapters, the parameters of interest are the race of the victim (first level) and the district's population probability distribution (second level). At the first level of the model both statistical bias (Arrow, 1973) or preference-based discrimination (Becker, 1957) can arise. If the estimated coefficient of the race of the civilian is positive and statistically significant, we have evidence that the police officer has either SBD or RBD towards black and brown people. However, at the second level of the model, in which the police officer uses a prior knowledge about the population of the district to act, the assumption is that we only observe statistical bias discrimination. In the case where the estimated coefficient of the percentage of the district's population that is either black or brown is negative (in the nighttime, the uncertainty regarding the civilian characteristics is larger than in the daytime) and statistically significant at conventional levels, we have evidence of statistical bias discrimination. Table 7 summarizes how we identify racial bias or statistical bias in the estimated coefficients in both levels of the hierarchical model.

Table 7: Interpretation of the estimated coefficients in terms of RBD and SBD across two hierarchical levels

	First level			
	Statistically significant		Not statistically significant	
	+	-	+	-
Race of the victim	Evidence of RBD and/or SBD	Evidence of “reverse” RBD and/or SBD	No evidence of RBD and/or SBD	
	Second level			
Percentage of the district’s population that is black or brown	Statistically significant		Not statistically significant	
	+	-	+	-
	Evidence of “reverse” RBD and/or SBD	Evidence of SBD	No evidence of RBD and/or SBD	

Source: prepared by the authors.

Assuming the causal model in equation 4.3, to better illustrate the interpretations let us present some hypothetical cases:

(i) $\hat{\beta}_1^{REML} > 0$ and statistically significant at conventional levels of significance, while $\hat{\beta}_2^{REML}$ is not statistically significant: we would interpret as evidence of racial bias discrimination and/or statistical bias discrimination. In this case, the police officer is more likely to kill a black or brown civilian when he/she can see the race of the victim (“light time”). However, due to lack of data about the outcomes of the police-civilian interactions, we cannot identify the type of discrimination.

(ii) $\hat{\beta}_1^{REML} < 0$ is statistically significant at conventional levels of significance, while $\hat{\beta}_2^{REML}$ is not statistically significant: evidence of “reverse” RBD and/or SBD. In this scenario, the police officer is more likely to kill a white civilian when he/she can see the race of the victim (“light time”).

(iii) $\hat{\beta}_1^{REML}$ is not statistically significant, while $\hat{\beta}_2^{REML} < 0$ is statistically significant at conventional levels of significance: in this case, we have evidence of statistical bias discrimination. During “darkness”, when the police officer cannot see the race of the victim, he/she has a larger probability of committing homicides in districts with larger concentration of black and/or brown individuals.

(iv) $\hat{\beta}_1^{REML} > 0$ and $\hat{\beta}_2^{REML} < 0$, both statistically significant at conventional levels of significance: evidence of both RBD and/or SBD but we cannot identify which.

(v) $\hat{\beta}_1^{REML}$ and $\hat{\beta}_2^{REML}$, both not statistically significant at conventional levels of significance: no evidence of either RBD and/or SBD.

At the first level of the hierarchical model, the variable linked to the race of the victim shows estimated coefficients not statistically significant at conventional levels of significance (90% confidence interval) in all three different specification models. The results of hierarchical structure show that, when controlling for other covariates that can help explain the disparity between individuals and incidents, the fact that a person is black or brown does not help explain the behavior of police officers in the decision to kill an individual. In other words, when the police officer can clearly identify the race of the victim (during daylight) compared when he cannot (during nighttime, raining and not in avenues), the probability of the police officer killing a black or brown individual is not statistically different than the probability of the police officer killing a white individual. Therefore, such result indicates that there is no evidence of either preference-based discrimination or statistical bias discrimination in the police behavior at the first level of the model.

One possible explanation for such findings is that the distribution of the racial groups of the Military Police officers of the State of São Paulo is remarkably similar to the distribution of the population's racial groups of the State. As cited in chapter 3, the percentage of the police officers that declare themselves as either black or brown (34.6%) is almost identical of the percentage of the State population that declares themselves as belonging to the same races. Our hypothesis is that a white police officer is less likely to discriminate if together with a fellow black or brown officer, and it is not likely that a black or brown police officer will discriminate against a civilian of the same race group as his/her. For instance, investigating racial discrimination in automobile crashes in the United States, West (2018) found evidence that police officers were more likely to discriminate if their race were different from their own.

At the second level of the hierarchical model, the proportion of the total black and brown population in the total population of the district j is negative and statistically significant in Model 1. This means that in districts in which there is a high concentration of black and brown individuals the police are less likely to kill during the daylight. On the other hand, police are more likely to commit homicides during the nighttime in districts where there is larger percentage of black and brown population. Therefore, we can interpret this as evidence of statistical bias discrimination against black and brown individuals.

In an uncertainty environment and context (nighttime periods in locations with poor visibility, i.e., higher risk for the police officer in the job), the risk averse police officer might be influenced by a prior knowledge that he has about the district. If the police officer has a prior belief that black and/or brown individuals are more prone to violence (statistical bias discrimination), districts with larger proportions of the population being black or brown leads to more violent actions by the police, because the latter believes those places have more risk associated with it. A negative coefficient of the proportion of the population in the district that is black or brown means that during the night the police kill more in districts where this proportion is higher when compared to the daytime period. Therefore, we argue that a negative estimated coefficient of the proportion of black and/or brown individuals in the district's population (second level), associated with a not statistically significant coefficient of the race of the victim at the first level, could be interpreted as evidence of statistical bias discrimination (SBD). The results on Table 6 show that we found evidence of statistical bias discrimination in all three models.

In order to give a clearer interpretation of the negative signal at the second level of the model, we inverted the definition of the dependent variable, meaning now homicide committed by the police during nighttime. Table 8 shows the estimated results.

Table 8: Results of the hierarchical models inverting the dependent variable

	Model 1	Model 3	Model 5
First level (racial bias and/or statistical bias)			
$Black\ and\ brown_i$	0.004 (0.031)	.	.
$Black_i$		0.062 (0.052)	.
$Brown_i$	.	.	-0.010 (0.032)
Second level (statistical bias)			
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	0.196*** (0.076)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	2.374** (1.187)	.
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	0.437** (0.171)
Year fixed effect	Yes	Yes	Yes
Log Likelihood	-852.03	-355.2	-757.11
AIC	1746.0	756.1	556.2
χ^2	11.409*	15.618**	11.584*
N	1,196	508	1,066
Number of groups		96	

Source: Prepared by the authors.
Note: standard error in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model.

As it can be seen, when the dependent variable assumes value 1 if the homicide committed by the police happened during the night, in rainy days and in places with poor public lighting, the probability of the police officer killing a civilian is larger in districts where the percentage of the population that is black and (or) brown is greater.

Controlling for observed and unobserved factors, we find no evidence of racial bias discrimination, but we find evidence of statistical bias discrimination in the capital city of the state of São Paulo at the second level of the hierarchical structure. This means that the risk averse police officers are more prone to discriminate in neighborhoods where there is a sizable percentage of the population that is either black or brown.

6. ROBUSTNESS CHECKS

In this chapter we present a series of robustness checks to validate the main results of the hierarchical model in the last chapter.

First, we focus only on the individual level (first level of the hierarchical structure), employing linear probability models, conventional Logit models, Probit models and Logit models estimated using a Bayesian approach. In this section, we also address the assumption of "bad apples" postulated recently by Lieberman (2020). Second, we extend this idea of "bad apples" to the hierarchical structure. Third, we test for an alternative to the external instrumental variable using the internal instruments in a hierarchical model framework proposed by Kim and Frees (2007). At last, we extended our sample for the metropolitan area of the capital of the State of São Paulo, which consists of 38 municipalities plus the capital city of São Paulo. The goal with this analysis is to check for the edge effects and to assess if the results found for the capital city only remains valid, using an ecological model with aggregated data of the districts and the surrounding cities of the metropolitan area of São Paulo.

6.1 Checking for both the racial bias discrimination and statistical bias discrimination at the individual level

In this section, we focus the analysis on the individual level (first level in the hierarchical structure), in which we can assess both the statistical bias (Arrow, 1973) and the preference-based discrimination (Becker, 1957) in the police behavior.

Lieberman (2020) discusses the idea of "bad apples", meaning that a few police officers could be responsible for the majority of the racial discrepancies in the data. Incorporating this hypothesis in our analysis, we included police station fixed effects in the models, as we will discuss further later on.

This section is divided in two parts. The first one is dedicated to frequentist approaches, which includes the estimation of linear probability models (LPM), Probit, and Logit models, as estimated by Fryer (2019) and Coviello and Persico (2015). The second includes a Logit model estimated in a Bayesian manner with uninformative prior distributions. Since the 1990s, there is a growing literature on Bayesian methods after the improvement of sampling algorithms, such as the Markov Chain Monte Carlo (MCMC), that allowed to drawn inferences about the posterior distributions (Gelfand and Smith, 1990).

6.1.1 Linear Probability Model, Probit and Logit Models

Considering the base model defined in equation 6.1, we start our analysis with an ordinary least squares (OLS) estimation of the following:

$$y_i = \beta_0 + \beta_1 black\_brown_i + \alpha X_i' + \gamma_{PS} + \varepsilon_i \qquad (6.1)$$

Note that equation 6.1 includes a fixed effect, γ_{PS}, which represents a fixed effect for the police station where the homicide was registered. Lieberman (2020) proposes the idea that the author called "bad apples", meaning that the racial bias observed in the data could be a result of only a small number of police officers that have a racial bias behavior. Since we do not have data regarding the police officer responsible for the homicide, we included police station fixed effects in the model. In the State of São Paulo, the Military police officer or the Civil police officer are assigned to work at a specific police station. Therefore, we aim to capture the effect of "bad apples" via police stations fixed effects.

In the main results, the police station fixed effect is captured via the intercept at the second level of the hierarchical structure, which encapsulates the district's fixed effect. The locations of the police stations did not alter much in the last ten years, so a district fixed effect would capture much of the police station fixed effect.

Table 9 shows the results of the linear probability models estimated using Ordinary Least Squares.

Table 9: Results of the linear probability model (OLS)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Black or Brown	-0.016 (0.030)	0.018 (0.030)	.	.	.	.
Black	.	.	-0.075 (0.055)	-0.029 (0.057)	.	.
Brown	.	.		.	-0.005 (0.029)	0.030 (0.030)
Not working	.	0.045 (0.044)	.	0.030 (0.062)	.	0.037 (0.047)
Slum	.	0.079 (0.090)	.	0.069 (0.123)	.	0.170 (0.238)
Wind	.	-0.017 (0.027)	.	0.008 (0.037)	.	-0.016 (0.030)
Temperature	.	-0.005 (0.004)	.	-0.004 (0.008)	.	-0.003 (0.005)
Intercept	0.537*** (0.029)	0.500 (0.301)	-0.537*** (0.029)	1.098*** (0.194)	0.537*** (0.029)	0.465 (0.295)
Year fixed effect	No	Yes	No	Yes	No	Yes
Police Station fixed effect	No	Yes	No	Yes	No	Yes
N	1,203	1,196	508	508	1,066	1,066
R^2	0.001	0.134	0.004	0.209	0.001	0.146

Source: Prepared by the authors.

Note: Robust standard errors clustered by districts in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model.

We used six different specifications of the Linear Probability models. In models 1 and 2, the variable of interest is a dummy variable equal to one if the victim of the homicide committed by the police officer was black or brown, and zero otherwise. In models 3 and 4, the definition of the dummy variable is changed in the sense that we want to see the impact of the victim being only black, so the variable of interest is defined as equals one if the victim was black, and zero otherwise. In models 5 and 6 the same is done when the victim was brown. Given that the race of the victim is based on police reports, the reason for these different specifications is to see if there is difference among them.

The results of the linear probability model considering only individual characteristics show no statistically significant effect in the estimated coefficient of the race of the victim. This means that, when the police officer has a clear view of the victim (during daylight), there is no statistically significant impact of the race of the victim in the decision of the police officer to commit a homicide. In other words, we do not find evidence of racial bias in police behavior when considering only characteristics of the victim.

One drawback of using a linear probability model is that the probability of the response is assumed to be linear in the parameters, which could implicate in estimated values of dependent variable being out of the 0-1 range, and therefore, cannot be characterized as probabilities.

To contour this problem, we redesigned equation 6.1 to characterize a Logit model as specified in equation 6.2:

$$y_i = G(\beta_0 + \beta_1 black\_brown_i + \alpha X_i' + \gamma_{PS} + \varepsilon_i) \tag{6.2}$$

where *G* is a function that assumes only values between 0 and 1. In the specific case of the logit model, the *G* function is the logistic function as shown in equation 6.3:

$$y_i = \frac{exp\ (\beta_0 + \beta_1 black\_brown_i + \alpha X_i' + \gamma_{PS} + \varepsilon_i)}{1 + exp\ (\beta_0 + \beta_1 black\_brown_i + \alpha X_i' + \gamma_{PS} + \varepsilon_i)} \tag{6.3}$$

And in the case of the probit model, the *G* function is the cumulative standard normal distribution function, as shown in equation 6.4:

$$y_i = \Phi(\beta_0 + \beta_1 black\_brown_i + \alpha X_i' + \gamma_{PS} + \varepsilon_i) \tag{6.4}$$

where $\Phi(z)$ is the standard normal density function as follows:

$$\Phi(z) = \frac{1}{\sqrt{2\pi}} e^{\left(\frac{z^2}{2}\right)} \tag{6.5}$$

Table 10 shows the results of the estimations using maximum likelihood of equation 6.3 (logit models), while Table 11 shows the results for the estimations of equation 6.4 (probit models).

Table 9: Results of the Logit model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Black or Brown	-0.062 (0.119)	0.081 (0.140)	.	.	.	.
Black	.	.	-0.302 (0.221)	-0.086 (0.248)	.	.
Brown	.	.		.	-0.018 (0.118)	0.133 (0.138)
Not working	.	0.211 (0.207)	.	0.155 (0.267)	.	0.175 (0.223)
Slum	.	0.362 (0.418)	.	0.301 (0.625)	.	0.813 (0.537)
Wind	.	-0.079 (0.126)	.	0.056 (0.182)	.	-0.078 (0.140)
Temperature	.	-0.024 (0.019)	.	-0.021 (0.033)	.	-0.014 (0.021)
Intercept	0.148 (0.115)	0.072 (1.510)	0.148 (0.115)	0.251* (0.134)	0.148 (0.118)	-0.121 (1.472)
Year fixed effect	No	Yes	No	Yes	No	Yes
Police Station fixed effect	No	Yes	No	Yes	No	Yes
N	1,203	1,196	508	508	1,066	1,066
McFadden R^2	0.001	0.111	0.003	0.181	0.001	0.121

Source: Prepared by the authors.

Note: Robust standard errors clustered by districts in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model.

Table 10: Results of the Probit model

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Black or Brown	-0.039	0.053	.	.	.	.
	(0.074)	(0.086)				
Black	.	.	-0.189	-0.093	.	.
			(0.138)	(0.166)		
Brown	.	.		.	-0.011	0.083
					(0.074)	(0.085)
Age		.	.	.	.	.
Not working	.	0.122		0.087	.	0.101
		(0.127)		(0.188)		(0.136)
Slum	.	0.217	.	0.195	.	0.480
		(0.260)		(0.386)		(0.086)
Wind	.	-0.048	.	0.028	.	-0.047
		(0.077)		(0.113)		(0.321)
Temperature	.	-0.015	.	-0.012	.	-0.009
		(0.012)		(0.022)		(0.013)
Intercept	0.092	-0.085	0.092	0.260*	0.092	-0.001
	(0.072)	(0.417)	(0.072)	(0.620)	(0.721)	(0.362)
Year fixed effect	No	Yes	No	Yes	No	Yes
Police Station fixed effect	No	Yes	No	Yes	No	Yes
N	1,203	1,196	508	508	1,066	1,066
AIC	1668.2	1682.1	708.18	767.01	1488.4	1503.1

Source: Prepared by the authors.

Note: Robust standard errors clustered by districts in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model.

Considering the conventional level of 90% confidence interval, in terms of statistical significance, the results of Tables 9, 10 and 11 are quite similar. One limitation of the OLS estimations and the Logit and Probit models estimated using maximum likelihood is that both models do not take environment-related variables into account in the estimations, which could lead to a potential omitted variable bias.

6.1.2 Bayesian approach

Using the data described in the chapter 4, we employed a Bayesian binary regression model (Collet, 1994) to explain the probability of the binary response variable y_i as a function of some covariates, including the race of the victim:

$$y_i|\pi_i = Ber(\pi_i) \tag{6.6}$$
$$\pi_i = Pr\ Pr\ (y_i = 1) \ = F(X_i'\beta) = \frac{exp\ (X_i'\beta)}{1 + exp\ (X_i'\beta)}$$

where y_i follows a Bernoulli distribution and is equal to one if the homicide i was committed by a police officer during daylight, and zero if it was committed by a police officer during nighttime in places with poor visibility. Therefore, the idea is to model the probability, π_i, of being killed by the police during the day as a function of the covariates at the individual level. The coefficient β is the *K* vector of unknown parameters, X_i' is the *K* matrix of known covariates associated to the *ith* individual. The linking function defines the linear predictor as:

$$\eta_i = F^{-1}(\pi_i) = \beta_0 + \beta_1 black\_brown_i + \beta_2 at\_work_i + \beta_3 slum_i + \beta_4 wind_i + \beta_5 temperature_i \tag{6.7}$$

The likelihood function for data $Y = (y_1, \ldots, y_n)'$ is:

$$P(Y|\beta) = F^{-1}(\pi_i) = \prod_{i=1}^{n} [F(X_i'\beta)]^{y_i}[1 - F(X_i'\beta)]^{(1-y_i)} \tag{6.8}$$

As pointed out by Souza and Migon (2004), it is necessary to provide a joint prior distribution over the parameter space in the Bayesian approach. This is not an easy task, given that the relationship between the data and the parameters is overly complex. Given the fact that we are dealing with a topic of causality, the easiest way to circumvent this difficulty is to propose an informative prior, but with small precision, avoiding any complaint about the specification of subjective beliefs (O'hagan, Woodward, and Moodaley, 1990). We followed the specification of Souza and Migon (2004) and we set informative, independent normal priors, with extremely small precisions to all the parameters in the model ($\beta_i \sim N(0,10)$). Therefore:

$$P(\beta|Y) \propto p(\beta) \prod_{i=1}^{n} [F(X_i'\beta)]^{y_i}[1 - F(X_i'\beta)]^{(1-y_i)} \tag{6.9}$$

Clearly, equation 6.9 is a complex function of the parameters and thereby numerical methods are needed to obtain the marginal posterior distribution for the parameters. Approximations can be made using simulation methods such as Markov Chain Monte Carlo methods (MCMC) or using a deterministic algorithm, for example, through Laplace methods. We chose the first method, namely, through the Metropolis-Hastings algorithm.

Table 12 exhibits the results regarding the estimations of the posterior distributions.

Table 12: Results of posterior distributions

	Posterior mean	Lower 90%	Upper 90%
Intercept	1.0 (0.5)	0.4	1.7
Black and brown	0.1 (0.1)	-0.1	0.3
Not working	0.0 (0.1)	-0.2	0.2
Slum	0.1 (0.5)	-0.6	0.7
Wind	-0.2 (0.1)	-0.3	-0.1
Temperature	0.0 (0.0)	0.0	0.0
N		1,196	
Posterior sample size		4000	

Note: prepared by the author.

Estimations were conducted via Monte Carlo Markov Chains. Prior distributions were adopted for all predictors N(0, 10).

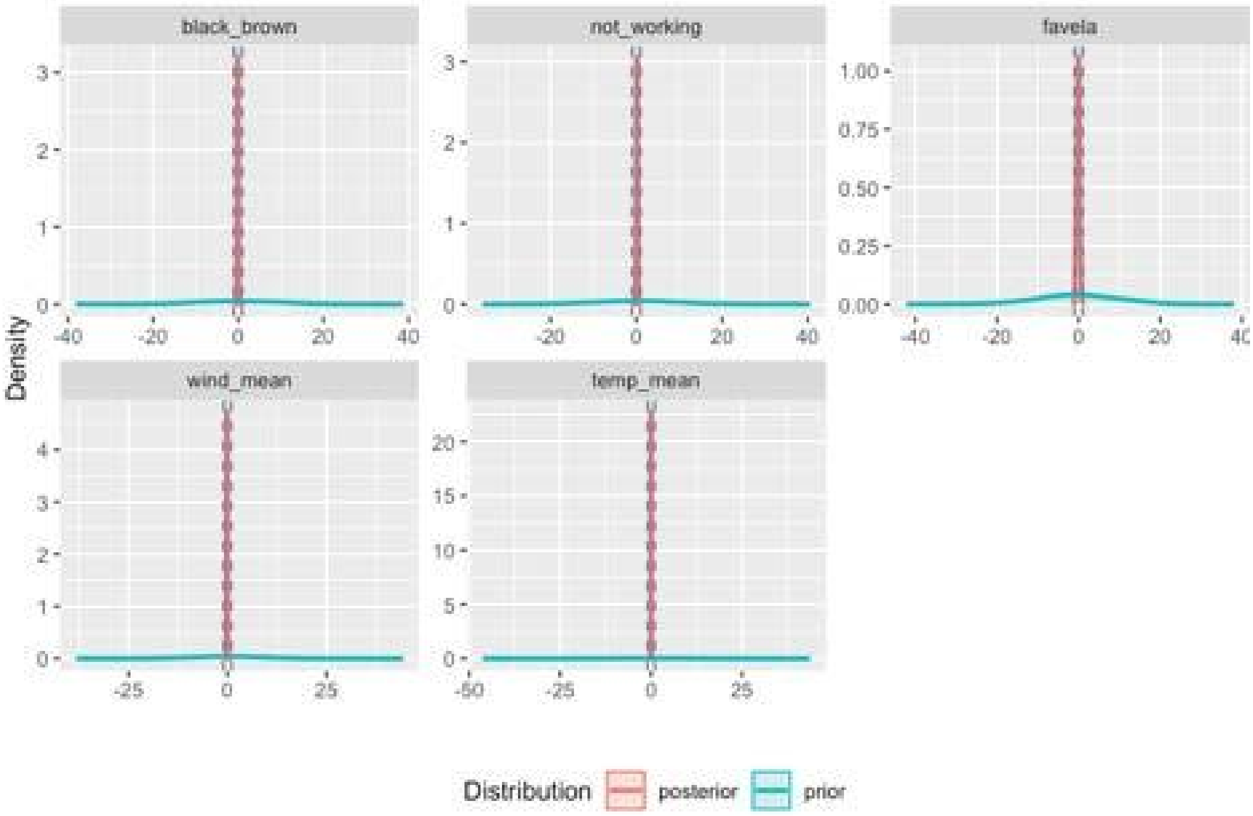
Using the Bayes Factor to test the hypothesis that the mass of the posterior distributions has shifted further or closer to the null value of zero relative to the prior distribution, indicates if the null value has become less or more likely given the observed data. The Bayes factor can be thought as an odds ratio representing the increase in the chance of the null hypothesis being more plausible than the alternative hypothesis after looking at the data in relation to your a priori opinion. A Savage-Dickey density ratio was computed, which approximates a Bayes factor comparing the marginal likelihoods of the model against a model in which the tested parameters have been restricted to the zero-null point (Figure 9). Table 13 shows the results of the test.

Table 13: Bayes Factor

	Bayes Factor
Intercept	0.002
Black and Brown	1.29e-9
Not working	3.21e-9
Slum	8.61e-4
Wind	1.24e-9
Temperature	0.000

Note: prepared by the author.

Figure 9: Bayes Factor



Source: prepared by the authors.

A Bayes factor greater than 1 can be interpreted as evidence against the null. Given the results found, we have strong evidence against the null only for the variable related to the fact of the police officer was at work when he killed someone. There is evidence in favor of the null hypothesis of value zero for the variable ‘black’. In other words, we do not find evidence that police officers are more racists during daylight.

Lieberman (2020) traces a parallel between schools and police stations. Characteristics of the schools often helps to explain the success of its students. For example, schools with better teachers tend to have students with better grades. That being said, Lieberman (2020) argues that the same could be valid for police stations. We investigate that through a hierarchical model in which we modified linking function as such:

$$y_i|\pi_i = Ber(\pi_i) \tag{6.8}$$

$$\pi_i = Pr\,Pr\,(y_i = 1) \ = F(X_i'\beta) = \frac{exp\,(X_i'\beta)}{1 + exp\,(X_i'\beta)}$$

$$\eta_i = F^{-1}(\pi_i) = \beta_{0PS} + \beta_1 black\_brown_i + \beta_2 at\_work_i + \beta_3 slum_i + \beta_4 wind_i + \beta_5 temperature_i \tag{6.9}$$

$$\beta_{0PS} = b_0 + \nu_{0PS} \tag{6.10}$$

The hierarchical structure arises by means of the intercept, β_{0PS}, that can vary across the police stations, ν_{0PS}, *PS* stands for the latter, while i still represents the individual level. In other words, we let the intercept differ across police stations, and the uncertainty that we want to estimate arises through the $\nu_{0PS} \sim N(0, \tau^2)$. The rest of the notation remains the same. Table 14 presents the results of the posterior distributions using the Metropolis-Hastings algorithm.

Table 14: Results of posterior distributions

	Posterior mean	Lower 95%	Upper 95%
Intercept	-0.5 (1.0)	-1.7	0.7
Black and brown	0.1 (0.2)	-0.1	0.3
Not working	0.1 (0.2)	-0.1	0.3
Slum	0.1 (0.5)	-0.6	0.8
Wind	-0.2 (0.1)	-0.3	0.0
Temperature	0.0 (0.0)	0.0	0.0
N		1,196	
Posterior sample size		4000	

Note: prepared by the author.

As we can see in Tables 12 and 14, the results of the hierarchical model are no different than the non-hierarchical. There is no significant effect regarding the color of the victim in the police officer behavior. Consequently, there is no evidence of racial bias discrimination (RBD) or statistical bias discrimination (SBD) when we consider only variables at the individual level (first level).

6.2 Checking for the "bad apples" effect

In the main specification presented in equation 4.3 in chapter 4, we did not include police station fixed effect, γ_{PS}, that we assume as a control for the "bad apples" effect (Lieberman, 2020). The theoretical reason behind this decision is that the locations of the police stations in the city of São Paulo are somewhat constant over time. Therefore, a fixed effect of the districts captures some of the information about the locations of the police stations.

However, there is another restriction that led to the decision of not including the police station fixed effect in the main specification. The optimal estimation methods to estimate the variance components of the hierarchical model expressed by equation 4.3 are either maximum likelihood (ML) or restricted maximum likelihood (REML). The main difference between the two is that the ML estimator does not include the degrees of freedom when estimating the variance components, while the REML includes the degrees of freedom in likelihood function (Tom, Bosker, and Bosker, 1999).

Unlike OLS estimations that have an analytical solution to the optimization problem for finding the best fitted parameters, the maximum likelihood estimation procedure relies on numerical approximations to obtain the best estimated parameters.

The ML estimation is based on an iterative process that updates the optimal parameters in each iteration until there is convergence in the maximum value of the likelihood function. A misspecified model can result in the non-convergence of the estimation. When we include the police station fixed effects in the specification 4.3 in the hierarchical model, there is no convergence in the REML estimations.

To contour this problem and evaluate if there is any difference between including the district fixed effect than including the police station fixed effect, we modify equation 4.3 in the following way:

$$y_{ij} = \beta_0 + \beta_1 black\_brown_i + \beta_2 prop\_black\_brown_j + \alpha X_i' + \pi Z_j' + \gamma_{PS} + u_j \quad (6.11)$$

where the variables are defined as in chapter 4. Since the Hausman test reveals that the variable $prop\_black\_brown_j$ is exogenous, we estimate equation 6.11 using OLS with robust standard errors clustered by districts. Table 15 shows the results of the estimated models.

Table 15: Results of the hierarchical structure estimated using OLS

	Model 1	Model 2	Model 3
$Black\ and\ brown_i$	0.019 (0.030)	.	.
$Black_i$		-0.024 (0.058)	.
$Brown_i$	.	.	0.031 (0.030)
$Not\ working_i$	0.041 (0.043)	0.035 (0.062)	0.034 (0.046)
$Slum_i$	0.082 (0.094)	0.045 (0.121)	0.165 (0.109)
$Wind_i$	-0.012 (0.027)	0.003 (0.039)	-0.012 (0.030)
$Temperature_i$	-0.005 (0.004)	-0.005 (0.007)	-0.003 (0.005)
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	-0.810** (0.368)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	-0.965 (3.387)	.
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	-1.005** (0.468)
$Poverty_j$	0.461 (0.412)	-0.001 (0.586)	0.456 (0.429)
$Inequality_j$	-0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)
$Green\ area_j$	-0.263 (0.402)	-0.736 (0.702)	-0.230 (0.452)
$Homicide\ rate_j$	-0.002 (0.002)	-0.003 (0.003)	-0.002 (0.002)
$Spatially\ lagged\ homicide\ rate_j$	-0.004 (0.005)	0.001 (0.008)	-0.003 (0.005)
Intercept	1.253** (0.515)	-0.253 (1.039)	1.413** (0.588)
Year fixed effect	Yes	Yes	Yes
Police Station fixed effect	Yes	Yes	Yes
R^2	0.138	0.218	0.150
N	1,196	508	1,066

Source: Prepared by the authors.

Note: robust standard errors in parenthesis clustered by districts; *** p-value<0.01, **p-value<0.05, *p-value<0.10.

The dot indicates that the variable is not included in the model. The spatially lagged homicide rate is constructed using a spatial weights matrix of the five nearest neighboring districts.

Considering the estimated coefficients of the race of the victim ($Black\ and\ brown_i$, $Black_i$ and $Brown_i$), the results of Table 15 show no evidence of RBD and/or SBD considering that in neither of the three models those estimated coefficients are negative and statistically significant at conventional levels of significance. On the other hand, considering the racial probability distribution of the population's district, we found evidence of statistical bias discriminations against black and brown people in model 1, and against brown individuals in model 3. Those results corroborate the main results of the hierarchical model presented in chapter 5.

However, in model 2, the estimated coefficient of the variable $\frac{Total\ black\ population_j}{Total\ population_j}$ is no longer statistically significant in Table 15 compared to Table 6. Since the only specification change between the hierarchical model estimated in chapter 5 was to include the police station fixed effects, it is reasonable to assume that γ_{PS} captured some of the variance of the percentage of the district's population that is black. In this case, it is possible to assume that some police stations have more police officers than on average have a larger statistical bias discrimination when compared to the others. In other words, we cannot rule out the hypothesis of "bad apples" regarding the discrimination of black people.

6.3 Checking for both the racial discrimination bias and statistical bias at the individual level and district level using internal instruments

Given the results of the Hausman test presented in Section 5, in which we did not reject the null hypothesis of exogeneity of the percentage of the population's districts that is either black or brown, the main results of the spatial hierarchical model were estimated via REML. However, valid external instruments are usually not easy to find. In recent years, the literature evolved to create new statistical methods to correct endogeneity without the need of external instruments. They are called internal instrumental variable models (IIV). Examples of such methods can be found in Ebbes *et al.* (2005)[41], Lewbel (1997)[42], Lewbel (2012)[43], Park and Gupta (2012)[44], and Kim and Frees (2007).

Kim and Frees (2007) propose a GMM estimator to deal with endogenous variables in a multilevel structure. Since we are modeling the police behavior using a spatial hierarchical structure, this approach can be more suited than the others. The idea behind the method proposed by the authors is to build internal instruments to correct the endogeneity problem.

> "*When all model variables are assumed exogenous, the GMM estimator is the usual GLS estimator. While the GLS model assumes all explanatory variables are uncorrelated with the random intercepts and slopes in the model, fixed effects models allow for endogeneity of all effects but sweeps out the random components as well as the explanatory variables at the same levels. The more*

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[41] Latent instrumental variables approach.
[42] Higher moments methods.
[43] Heteroskedastic error models.
[44] Models based on joint estimations using copula.

> *general estimator presented here allows for some of the explanatory variables to be endogenous and uses this information to build internal instrumental variables. The multilevel GMM estimator uses both the between and within variations of the exogenous variables, but only the within variation of the variables assumed endogenous. The mixed GMM estimator equals the random effects estimator when all variables are assumed exogenous and is equal to the fixed effects estimator when all variables are assumed endogenous. In between, different GMM estimators are obtained for different sets of endogenous/exogenous variables. (Kim and Frees, 2007, p.12).”*

As a robustness check for our main external instrument (the distance between where the police officer committed the homicide and the district of Sé in the central part of the city), we included the estimation procedure of Kim and Frees (2007) using internal instruments to address the possible endogeneity of the proportion of the district’s population that is either black or brown. Table 16 presents the results.

Table 16: Results of the Hierarchical models via GMM estimator using internal instruments

	Model 1	Model 2	Model 3
	First Level		
$Black\ and\ brown_i$	-0.003 (0.031)	.	.
$Black_i$	.	-0.062 (0.052)	.
$Brown_i$	.	.	0.010 (0.032)
$Not\ working_i$	0.054 (0.034)	0.048 (0.054)	0.049 (0.036)
$Slum_i$	0.020 (0.097)	0.088 (0.128)	0.103 (0.108)
$Wind_i$	-0.106 (0.087)	-0.015 (0.137)	-0.134 (0.092)
$Temperature_i$	-0.118 (0.087)	-0.044 (0.133)	-0.094 (0.092)
	Second level		
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	-0.196** (0.076)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	-2.374** (1.187)	
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	-0.437** (0.170)
$Poverty_j$	0.042 (0.086)	-0.086 (0.121)	0.051 (0.088)
$Inequality_j$	0.044 (0.124)	0.354* (0.185)	-0.008 (0.125)
$Green\ area_j$	-0.043 (0.100)	-0.001 (0.131)	-0.039 (0.105)
$Homicide\ rate_j$	0.059 (0.075)	0.073 (0.110)	0.021 (0.076)
$Spatial\ lagged\ homicide\ rate_j$	0.128* (0.071)	0.287*** (0.100)	0.132* (0.073)
Year fixed effect	Yes	Yes	Yes
N	1,196	508	1,066
Number of groups		96	

Source: Prepared by the authors.
Note: standard errors in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model. Year fixed effects are present in all three models.

As we can see, the results did not have any major changes in the values of the estimated coefficients neither in their statistical significance. This result is in concordance with the main results shown in Table 6 and reinforces the lack of any statistically significant impact of the race of the victim (first level), and the statistically significant effect of the racial probability distribution of the neighborhood where the homicide happened (second level) in the police behavior. In other words, the results reassure that there is no evidence of racial bias in police behavior in the city of São Paulo, but we found out evidence of statistical bias at the second level of the hierarchical structure.

6.4. Edge effects

Despite the majority of the statistical theories has been developed under the assumption of an infinite space, spatial analysis is often carried out within a finite study region, bounded by line segments of an infinite space (Yamada, 2009). Because of this established bounded segment, a boundary is always present. However, any spatial event is likely to extend beyond its boundary due to spatial interactions with other events in the proximity. Therefore, a spatial analysis can be biased because of the ignorance of the events happening outside the bounded region. According to Yamada (2009, p. 381):

> *"Edge effects are important for any type of spatial analysis, including analysis of point and areal data, because methods for spatial analysis always require that spatial relationships between observations be defined based on their proximity, adjacency, or other criteria, which may be biased due to unrecorded observations located outside the study region."*

The metropolitan area of São Paulo is composed of 38 municipalities surrounding the city of São Paulo. It is one of the largest urban conglomerates of the world, concentrating more than 20 million inhabitants.

In this section, we extend the sample to include all the homicides committed by police officers in the metropolitan area of São Paulo. We aim to assess if the results found for the city of São Paulo only are the same for the entire Metropolitan area. The surrounding cities of the São Paulo are then considered as "districts" also. The goal in doing so is check for the presence of edge effects in our study area.

Table 17 shows the results of the hierarchical models estimated. We used the same specifications of Section 5.

Table 17: Results of the Hierarchical models for the metropolitan area

Dependent variable: Homicide committed by the police during daylight	Model 1	Model 2	Model 3
First level (racial/statistical bias)			
$Black\ and\ brown_i$	-0.012 (0.025)	.	.
$Black_i$		-0.038 (0.041)	.
$Brown_i$	.	.	-0.007 (0.026)
$Not\ working_i$	0.021 (0.027)	-0.015 (0.087)	0.024 (0.029)
$Slum_i$	-0.036 (0.066)	0.002 (0.087)	-0.011 (0.072)
$Wind_i$	-0.116 (0.074)	-0.007 (0.113)	-0.157** (0.078)
$Temperature_i$	-0.066 (0.079)	0.066 (0.120)	-0.049 (0.083)
Second level (statistical bias)			
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	-0.153** (0.061)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	-2.561** (1.035)	.
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	-0.313** (0.131)
$Poverty_j$	0.061 (0.080)	-0.219 (0.273)	-0.001 (0.216)
$Inequality_j$	0.045 (0.101)	0.279* (0.159)	0.017 (0.101)
$Green\ area_j$	0.001 (0.080)	0.012* (0.110)	0.006 (0.081)
$Homicide\ rate_j$	0.052 (0.072)	0.037 (0.109)	0.021 (0.072)
$Spatially\ lagged\ homicide\ rate_j$	0.114* (0.065)	0.234** (0.093)	0.126* (0.056)
Year fixed effect	Yes	Yes	Yes
AIC	2,680.8	1,167.6	2,394.1
Log Likelihood	-1,324.4	-562.8	-1,214.4
χ^2	10.514*	15.659**	10.717*
N	1,914	793	1,643
Number of groups		134	

Source: Prepared by the authors.
Note: standard error in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not included in the model.

The Hausman test to assess the endogeneity of the percentage of the district's population that is either black or brown was performed using the same instrumental variable. We fail to reject the null hypothesis of exogeneity using a confidence interval of 99% in all specifications. Therefore, the variable of the percentage of the district population that is black or brown, only black, or only brown is assumed to be exogenous, and we can estimate the models using REML.

As we can see in Table 17, we find evidence of statistical bias discrimination in the police behavior via the negative and statistically significant, at 95% confidence interval, coefficients of the percentage of the district's population that is black or brown, only black, and only brown in all three different specifications. With respect to the RBD and SBD at the individual level (first level of the hierarchical structure), we found no evidence of such effect, thereby corroborating with the previous results shown until now.

6.5. Checking for the statistical bias discrimination using an ecological model

In this subsection, an ecological model using the aggregated data from the 96 districts of São Paulo and the 38 municipalities of the metropolitan area (except the city of São Paulo) is estimated by OLS. Equation 6.12 summarizes the following:

$$homicide\_night_j = \delta_0 + \delta_1 prop\_black\_brown_j + \sigma Z_j' + \varepsilon_j \qquad (6.12)$$

The dependent variable, $homicide\_night_j$, is the number of homicides of black and brown individuals committed by police officers during the night, in rainy days and in places with poor public lighting (not in avenues) in the j district divided by the districts population and multiplied by 100,000. The matrix Z_j' is the same as the one of the second level in the hierarchical model with the addition of the variable of public lighting measured as the percentage of houses in the districts that have public lighting in the streets[45]. Note that 6.12 is a restricted SLX model since Z_j' contains the spatially lagged homicide rate in the districts to control for the spatial displacement of crime.

The interest lies on the δ_1 coefficient, meaning that we want to see the impact of the proportion of the district's population that is black or brown in the aggregated number of homicides committed by the Police during nighttime. Table 18 shows the results of the estimation of equation 6.12 using OLS.

[45] The source of this information is the Brazilian Census of 2010 conducted by the IBGE. Unfortunately, this variable is only available at the district level; hence, it is not possible to use as a source of information in the hypothesis of "veil of darkness".

Table 18: Results of the ecological model

	Capital area only			*Metropolitan region*		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$\frac{Total\ black\ and\ brown\ population_j}{Total\ population_j}$	21.791*** (5.091)	.	.	25.833** (5.671)	.	.
$\frac{Total\ black\ population_j}{Total\ population_j}$	.	115.552*** (31.991)	.	.	149.110*** (25.402)	.
$\frac{Total\ brown\ population_j}{Total\ population_j}$	.	.	24.481*** (6.003)	.	.	28.537*** (6.898)
$Poverty_j$	2.887 (5.245)	3.765 (5.206)	3.288 (5.318)	-3.811** (1.774)	-1.507 (1.851)	-4.352 (1.672)
$Inequality_j$	-0.004 (0.004)	-0.007* (0.004)	-0.003 (0.004)	-0.001 (0.004)	-0.007 (0.004)	0.001 (0.004)
$Public\ Lighting_j$	6.487 (7.309)	-2.295 (9.649)	8.615 (7.260)	2.443 (5.815)	-5.222 (6.168)	3.909 (5.989)
$Green\ area_j$	-3.524 (6.721)	-1.675 (8.378)	-5.250 (6.449)	3.707 (5.372)	5.247 (5.360)	2.206 (5.274)
$Homicide\ rate_j$	0.014 (0.030)	0.024 (0.033)	0.013 (0.030)	-0.002 (0.034)	0.009 (0.036)	-0.003 (0.033)
$Spatially\ lagged\ homicide\ rate_j$	-0.013 (0.071)	0.021 (0.076)	0.021 (0.071)	0.012 (0.106)	0.059 (0.111)	0.005 (0.105)
Intercept	-5.041 (7.092)	1.475 (7.419)	-5.207 (7.256)	-6.068 (7.320)	-1.007 (5.933)	-5.406 (7.611)
N		96			134	
R^2	0.361	0.323	0.357	0.160	0.140	0.153

Source: Prepared by the authors.

Note: robust standard error in parenthesis; *** p-value<0.01, **p-value<0.05, *p-value<0.10. The dot indicates that the variable is not present in the model.

Table 18 shows a strong evidence of statistical bias discrimination in all six different specifications through the positive and statistically significant estimated coefficients of the racial probability distribution in the districts and in the municipalities of the metropolitan area.

7. CONCLUSIONS

The aim of this dissertation was to shed some light between race and police behavior in Brazil. Movements like the Black Lives Matter has gained a lot of strength in recent years in the United States and a lot of debate has emerged to find some association between race and police behavior (Antonovics and Knight, 2009; Fryer, 2019; Lieberman, 2020; West, 2018).

Collecting data from the city of São Paulo for the years of 2013 to 2021, we employed a spatial hierarchical model to identify the causal link between the race of the victim of homicide by police officers in the city. Dividing the sample in two distinct groups based on the visibility that the police officer had during the time of the incident, we do not find evidence of racial discrimination bias (RDB) in the police behavior. However, variables associated with the location where the homicide happened had a statistically significant impact on police behavior. Specifically, the percentage of the district's population that is black or brown, which we interpret as evidence of statistical bias discrimination (SBD).

A few points of concerning limitations are necessary. First, our approach is designed to identify the extent of racial bias and statistical bias discrimination only in homicides. Data from non-lethal outcomes are needed if one wants to extend the analysis for this type of violence. Second, our empirical results apply only to the metropolitan area of São Paulo and should not be extended to other jurisdictions.

Testing for the "bad apples" effects as Lieberman (2020) did for the United States, showed no change in the results found. The "bad apples" hypothesis suggested that only a small fraction of the police officers has a racially biased behavior. We tested this hypothesis via a police station fixed effect, since in Brazil a police officer is often designated to work in a fixed police station and we do not have information about the police officer that committed the homicide, we only have information about the police station.

Another issue that we addressed is the edge effect, in which we analyze the effects of race in police behavior in the regions close to the city of São Paulo. We expanded our sample to include all the homicides committed by police officers in the 38 municipalities of the metropolitan area of São Paulo plus the districts of the city of São Paulo. The results corroborate with the ones found for the city of São Paulo only. In other words, we did not find evidence of racial bias discrimination at the individual level, but we found evidence of statistical bias discrimination at the population level.

The racial profile of the police officers is remarkably similar to the racial profile of the average population of São Paulo, around 35% of both police officers and the State population are either black or brown. Therefore, a police officer is not likely to discriminate against a civilian of the same race group as his or her own. Also, a white police officer that can be either racially or statistically biased against black or brown people is less likely to discriminate in the presence of a black or brown colleague.

In recent years, the public safety offices in Brazil, encouraged by the Federal Access of Information Law of 2011, promoted data transparency. The Public Safety Office of São Paulo currently make publicly available data about homicides committed by police in the State. However, there is still a long way to achieve the same level of transparency as we observe in Stop and Frisk program of New York. For instance, we do not have data about non-lethal interactions between civilian and police officers. Data transparency is crucial to fully understand the racial discrimination in police behavior. Previous literature (Fryer, 2019) found evidence of racial bias discrimination only in data of non-lethal interactions between police officers and civilians.

Designing public policies to mitigate discrimination committed by police officers is a crucial task to lead us to a better future where a person does not suffer any injustice solely because of his/her skin color. Recently, we have seen an adoption of body-worn cameras in Police Departments in the State of São Paulo and in the South Region of Brazil. The idea of using this kind of equipment is to impose a way to better monitor the police actions. Using a randomized controlled trial, Souza *et. al* (2021) assessed the impact of body-worn cameras by the police in the state of Santa Catarina. The authors found a reduction in the use-of-force and arrests, and an increase in crime reporting by civilian, via the monitoring of the police activity through body-worn cameras. The impact of using body-worn cameras by the police showed to be stronger on events classified ex-ante as of low seriousness, and junior police officers. Overall, the results presented by Souza *et. al* (2021) showed that de-escalates conflicts.

Given that effect, we argue that it could also be used as public policy with a potential to minimize the statistically biased policing in São Paulo.

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Appendix

A.1 Data

The main challenge of working with the criminal data from the police reports of São Paulo is the substantial data cleaning required to get a tidy version from the raw data. In this appendix, we show some additional exploratory analysis about the data collected.

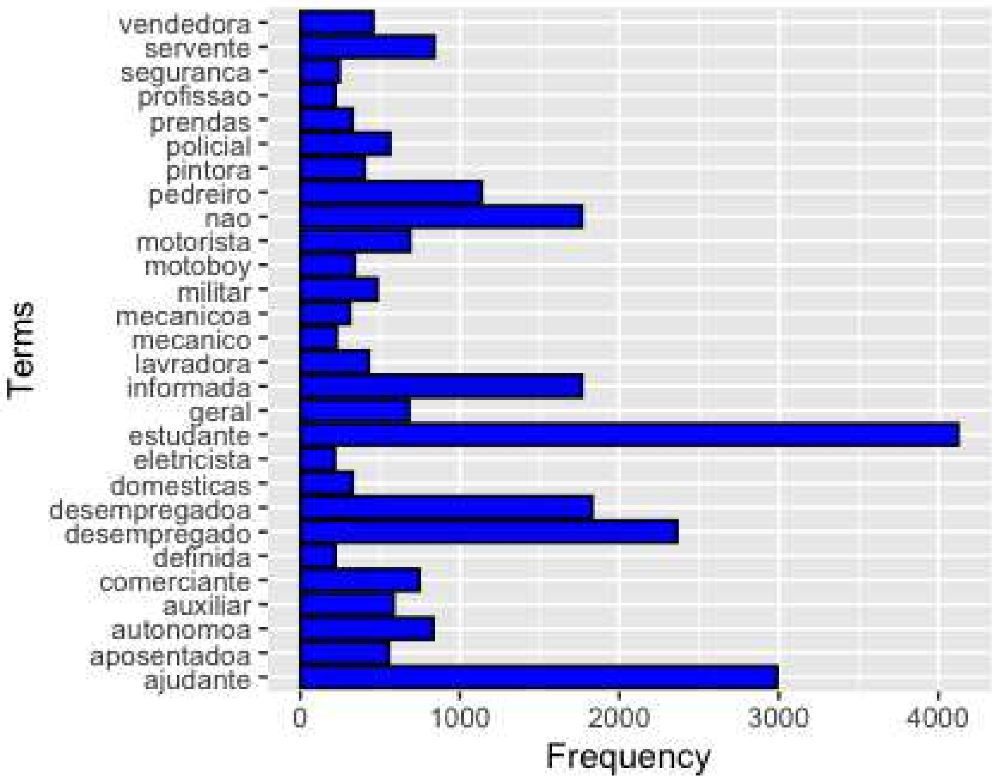
A text mining approach was applied to analyze the most common profession between the victims of homicide in the hands of police officers in the city of São Paulo. We assessed the most common terms that indicate the latter. Figure A1 shows a word cloud with the results.

Figure A1: Word cloud showing the occupations of the victims of homicides committed by the police.

Source: prepared by the authors.

The interpretation of a word cloud is the most intuitive as possible, the size of the word represents the frequency in which the term appeared in the police reports. The bigger the word, the higher the frequency of appearance. The same is valid for the opposite, the smaller the word, the smaller the frequency. Unfortunately, the police report terms are in Portuguese. However, as it can be seen, there is two bigger words in the middle "estudante" and "desempregado." If you know a little of Portuguese, these represents student and unemployed, respectively. Figure A2 corroborates the results of the word cloud and shows the frequency in which the terms appeared in the police reports.

Figure A2: Frequency of the terms referring to the occupation of the victims



Source: prepared by the authors.

Even though the majority of the victims of homicide by the police consisted of students and unemployed individuals, it is hard for the police officer to distinguish between those two professions and decide to shoot solely because of these characteristics. In other words, it is an implausible hypothesis that the police can distinguish which individuals are students or unemployed from the rest of the population just by looking at them. Therefore, it is not present in our models any variable linked to the profession of the victims.

A.2 Spatial Point Process

As it was argued in subsection 5.2.1, it is reasonable to assume that the homicides committed by the police are a spatial point process, which is a stochastic process governing the location of events $\{s_i\}$ in some set $D_s \subset R^d$. The number of such events in a subset of D_s is also random. It is common to have two types of points, in the case we are studying for instance, one type would be the homicides committed by police officers during daylight, and the other type is the baseline comparison group, the homicides committed by police officers during the "darkness" period. This type of point process is called marked point pattern because each point is assigned to a category and assigned accordingly. Also, several covariates can be associated with the phenomenon.

Considering only simple spatial processes[46] in R^d, we characterize the spatial point process Z through subsets $A \subset D_s \subset R^d$, which are Lebesgue measurable[47]. Let $Z(A)$ denote the number of events in $A \subset D_s$; then $Z(.)$ is a stochastic (counting process) that is defined on A. Then $\{Z(A): A \subset D_s\}$ characterizes the point process, assuming that D_s is bounded and that $Z(A)$ is finite for all $A \subset D_s$. A spatial point pattern can be characterized by its first and second order moments.

The first-order intensity function can be thought of as the expected number of occurrences in each region A. Let $\lambda(s)$ be the measure of the potential for an event to appear at any location $s \in D_s$. Given *ds* denoting a small region of *s* with volume |*ds*|, the first-order intensity function can be defined as:

$$\lambda(s) = \frac{E(Z(ds))}{|ds|}, s \in D_s \tag{A.2.1}$$

Provided that the limit exists. Hence,

$$E\big(Z(A)\big) = \int_A \lambda(s)ds, A \subset D_s \tag{A.2.2}$$

The second-order intensity function is given by

$$\lambda_2(s, x) = \frac{E(Z(ds)Z(dx))}{|ds||dx|}, s, x \in D_s \tag{A.2.3}$$

Diggle (1985) proposed the first kernel intensity estimator for point processes, incorporating an edge correction in the work of Rosenblatt (1956) and Parzen (1962). For a two-dimensional point process in the locations $\{s_1, \dots, s_m\} \in D_s$, the kernel estimator for $\lambda(.)$ is defined as such:

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[46] Simple spatial processes are defined as point patterns in which there can be no more than one occurrence of the event in the same location at the same time.

[47] Lebesgue measure regions are the ones that the d-dimensional measures are defined in the Euclidean space. In other words, Lebesgue measure regions have its dimensions defined and thereby a probability measure can be inferred.

$$\hat{\lambda}_t(s) = \frac{\sum_{i=i}^{m} \delta_t(s - s_i)}{p_t(s)}, s \in D_s \tag{A.2.4}$$

where $\delta_t(s) = t^{-1}\delta(t^{-1} - s)$ is a probability density function symmetric about the origin, and $t > 0$ is the bandwidth that determines the amount of smoothing. $p_t(s)$ is the edge correction defined as

$$p_t(s) = \int_{D_s} \delta_t(s - x)dx \tag{A.2.5}$$

It is obvious that in nonparametric methods we need to determine the smoothing parameter. While in the goodness-of-fit test we needed to determine the number of small regions, in the kernel estimator we need to choose the bandwidth size. The choice of *t* is based on the well-known trade-off between bias and variance and it has motivated a lot of discussion about how to determine the best degree of smoothness (Green, Seheult and Silverman, 1988; Marron, 1988; Scott, 2015). Recently, Borrajo, González-Manteiga and Martínez-Miranda (2020) proposed a kernel estimator using covariates with a smooth bootstrap procedure.

If the spatial point process is not a Homogenous Poisson Process (HPP), it is necessary to calculate the second order intensity function to fully characterize the process. One way is based on the distance between nearest events, also known as the *G* function. This function measures the distribution of distances from an arbitrary event to its nearest neighbor. Consider the second-order intensity function for two events $\lambda_2(s, x)$. If $Z(ds)$ and $Z(dx)$ are statistically dependent, then $\lambda_2(s, x) \neq \lambda(s)\lambda(x)$. Hence, $\lambda_2(s, x)$ can be used as a summary of measure of spatial dependence, and the pair-correlation function,

$$g(s, x) = \frac{\lambda_2(s, x)}{\lambda(s)\lambda(x)} \tag{A.2.6}$$

Is often used. Suppose that *Z(.)* is stationary and isotropic, then

$$\lambda(s) \equiv \lambda^0 \tag{A.2.7}$$

And

$$\lambda_2(s,x) \equiv \lambda_2^0(||s-x||), s, x \in D_s \tag{A.2.8}$$

Let $h = ||s-x||$ be the distance between events *s* and *x*. Then the pair-correlation function becomes

$$g^0(h) \equiv \frac{\lambda_2^0(h)}{(\lambda^0)^2}, h > 0 \tag{A.2.9}$$

The plot between the cumulative distributive function $g^0(h)$ and *h* can be used as an exploratory analysis of interaction between events. Small values of $g^0(h)$ occur if events at distance h-apart are rare; large values if close events occur frequently. In other words, if the plot of $g^0(h)$ versus h shows an exponential growth for small values of *h,* this indicates that the interaction between events at that scale are clustered. If the plot shows small values of $g^0(h)$ for small values of *h* and starts to grow faster for bigger h, this indicates a regular pattern. In order to construct the confidence interval of the test, Monte Carlo simulations are used.

An extension of the *g* function weighting by the intensity of the process, $\lambda(.)$ leads to a general definition of the *K* function proposed by Ripley and Kelly (1977). In this sense, define the $K(h)$ function as

$$K(h) = \frac{2\pi}{\lambda^0}\int_0^h x\lambda_2(x)dx \tag{A.2.10}$$

In other words, what the *K* function is calculating is the second-order intensity function of the process varying the distance radius *h*.

The value of the *K* function in case of completely random events is $K(h) = \pi h^2$ (which is the area of a circle with radius h). By comparing the estimated value $\widehat{K}(h)$ to the theoretical value in case of an HPP, it is possible to see the type of interaction that the point process has. It is usual to assume that these interactions occur at small scales. Therefore, the interest relies in small values of h. When $K(h) > \pi h^2$, there is evidence of clustered processes, whilst values smaller than the theoretical value of CSR is found, there is evidence of a regular pattern (Bivand, Pebesma, & Gómez-Rubio, 2013). Defining N_h as the number of events within distance event h of an arbitrary event *x*

$$K(h) = \frac{1}{\lambda^0} E(N_h), h \geq 0 \tag{A.2.11}$$

What the previous expression defines is that $\lambda^0 K(h)$ represents the expected number of extra events within h-distance. It is important to note that the *K* function does not uniquely define the point process because two different point process can be represented by the same $K(h)$ function. A standardized version of the *K* function is often used, and it is known as the *L* function.

$$L(h) = \sqrt{\frac{K(h)}{\pi}} - h \tag{A.2.12}$$

One of the issues with the *K* and *L* functions is the edge effect. Events outside the study region are not observed, which could lead to the estimations being negatively biased. The extra events for an event near the boundary of the region are not taken into account.

A.3 *Exploratory analysis of the spatial pattern of homicides committed by the police in São Paulo*

With the computational power rapidly evolving, we see more frequently each day spatial data being available to us, and now more than ever we can analyze and make inferences using those data. There are two main interests when working with spatial data: the structure of the underlying events and the possible interaction between them (Almeida, 2012; Bailey and Gatrell, 1995; Bivand, Pebesma, and Gómez-Rubio, 2013).

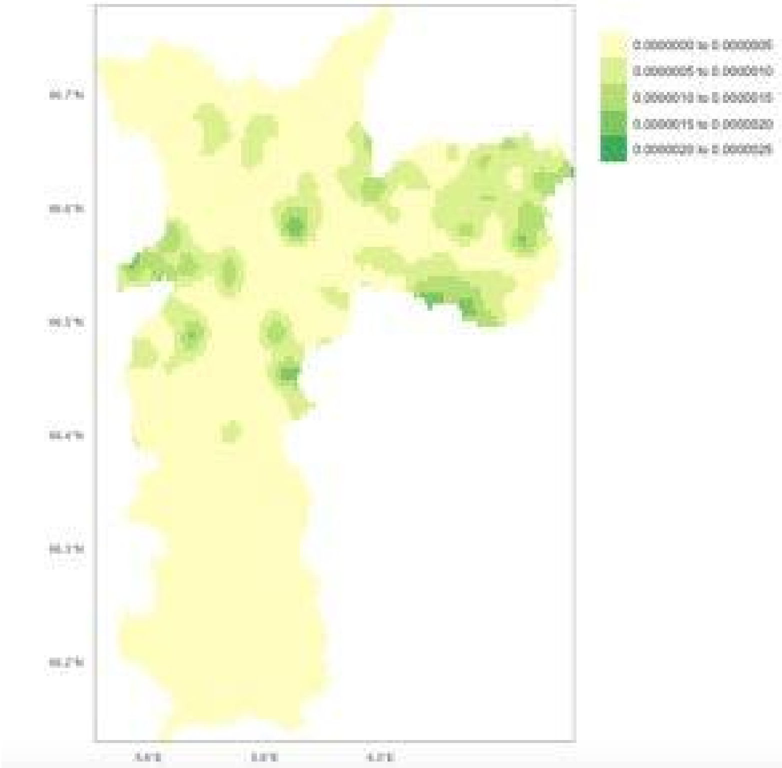
A crime can happen for several reasons, and the discussion about what are the incentives of an individual to commit a crime can be traced back to Becker (1968). It is reasonable to assume that their locations are the result of a superposition of many chance occurrences, and hence they can be modeled as a spatial point process.

The analysis of point patterns is focused on the spatial distribution of the observed events and making inference about the underlying process that generated them (Diggle, 2003). In particular, there are two main issues of interest: the distribution of events in space (first-order intensity function) and the existence of possible interactions between them (second-order intensity function).

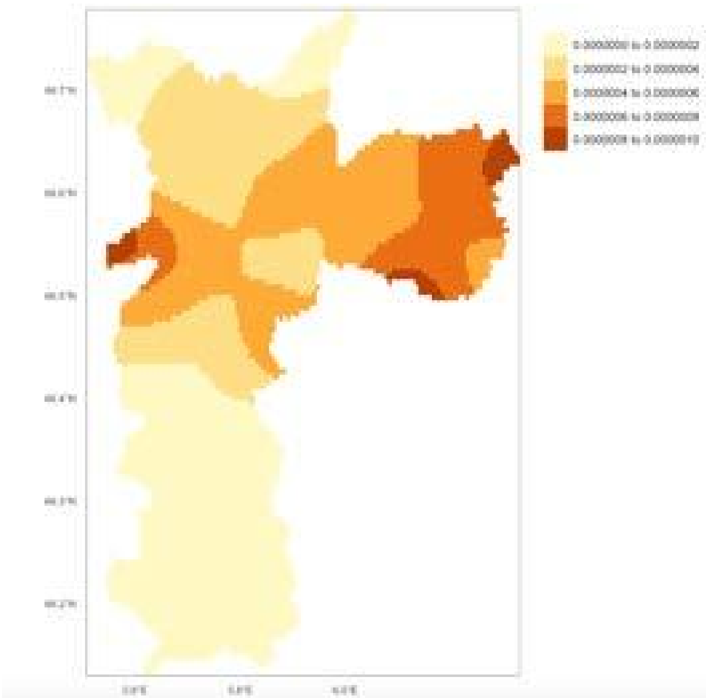
The first thing to do when dealing with a spatial point process is to test for completely spatial random (CSR). There is basically two main ways of testing if the point pattern is a Homogeneous Poisson Process. One is known as the Quadrat method test and the other is the kernel estimation. It is important to emphasize that both are nonparametric methods to determine the first-order intensity function of the process.

Figures A3 and A4 are the results of the Kernel estimator using the bandwidth proposed by Diggle (1985) and by Scott (2015) to analyze the first-order moments of both homicides committed by police officers during daylight, in days with good visibility (days with no rain), and homicides committed by the police during nighttime, in days with poor visibility (rainy days and not in avenues where there is usually good public lighting).

Figure A3: Kernel estimations of the homicides committed by police officers during daylight with good visibility



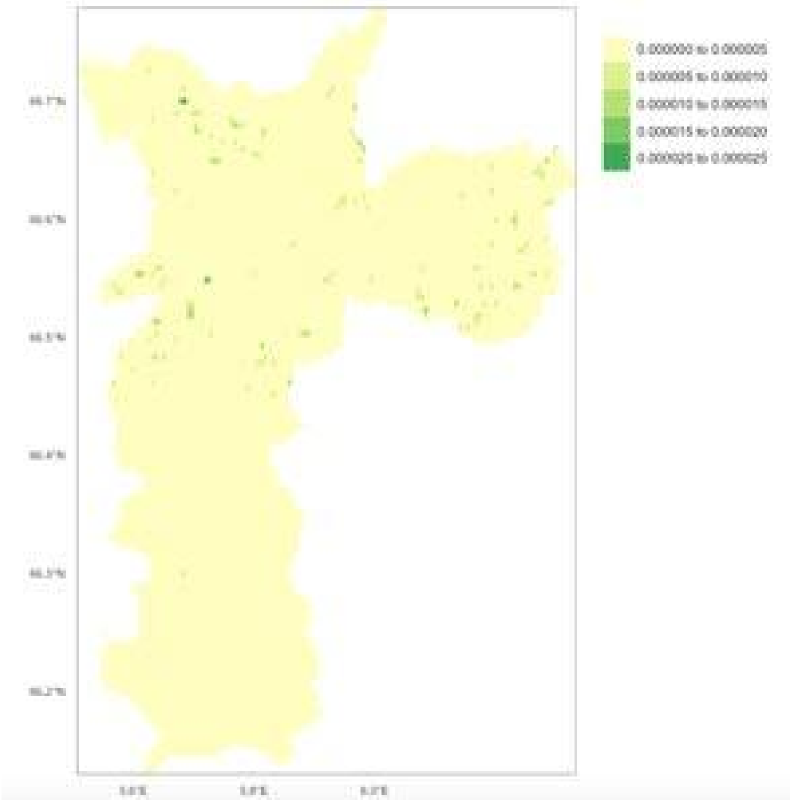
a. Diggle (1985) bandwidth



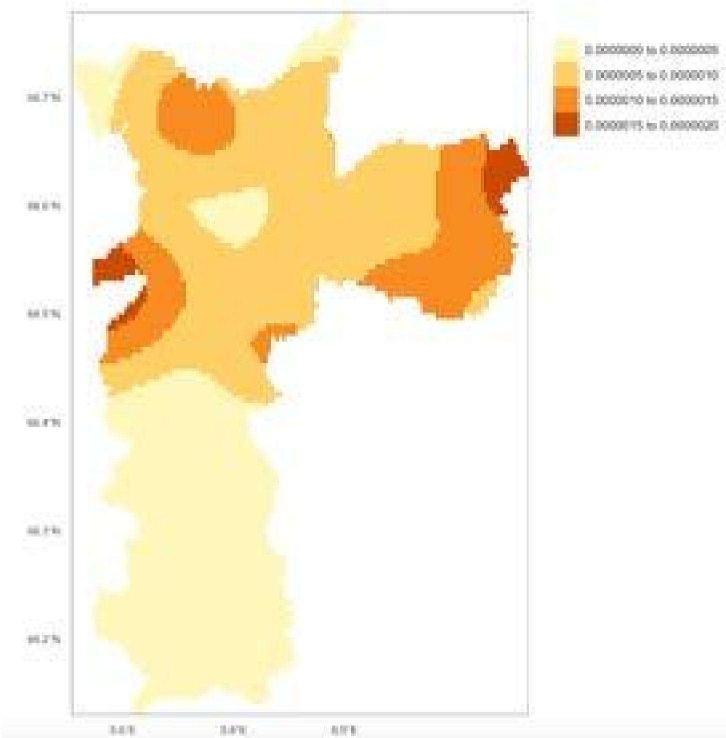
b. Scott (2015) bandwidth

Source: prepared by the authors.

Figure A4: Kernel estimations of the homicides committed by police officers during nighttime in days with poor visibility



a. Diggle (1985) bandwidth



b. Scott (2015) bandwidth

Source: prepared by the authors.

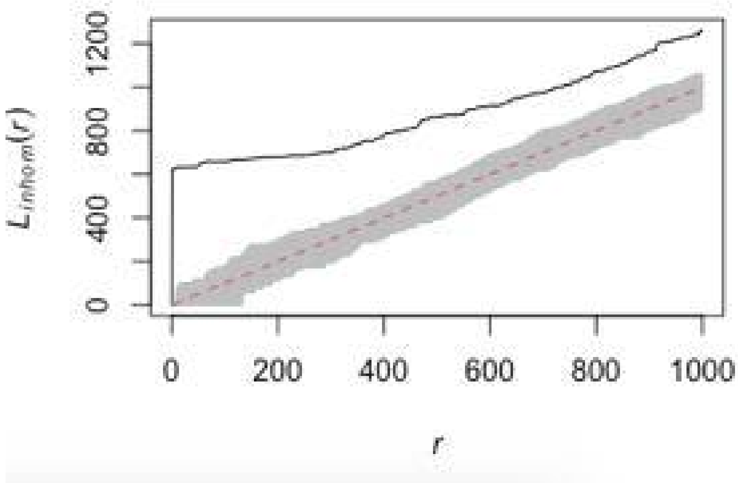
The interpretation of the kernel estimations is quite intuitive: it can be thought as the number of events in a circle. More points inside the circles, more vivid colors in the maps. Usually, the Diggle (1985) bandwidth produces smaller radius of the circles than the one proposed by Scott (2015). The choice of the bandwidth is intrinsically linked to the classical bias-variance tradeoff, smaller bandwidths are associated to less bias but high variance, while larger bandwidths are linked to more bias but less variance.

The results of the kernel estimations show that both the point processes of homicides committed by police officers during daytime in days with good visibility as the ones committed during the night in days with poor visibility are neither isotropic nor uniformly distributed. The first-order intensity function is inhomogeneous computed using the bandwidth proposed by Diggle (1985) and by Scott (2015), for both point processes, meaning that the data is not completely spatially random, so there is an underlying spatial structure to be modeled. It is also important to notice that there is a concentration of points in the north part of the city, especially in the northeast.

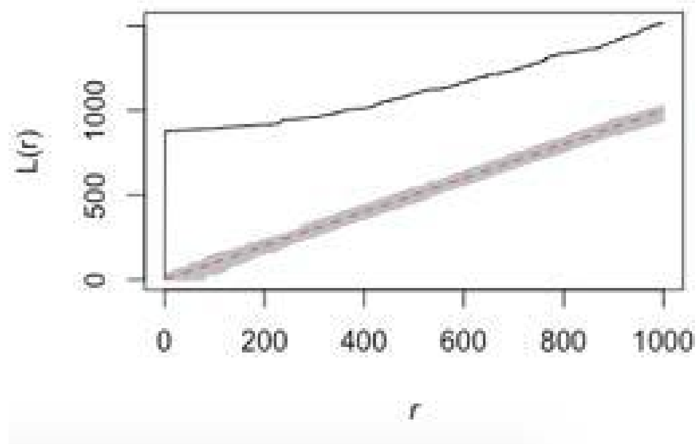
In order to completely define the point process, it is necessary to determine the second-order intensity function. We used the L-function to determine the interaction between events of the same category, as well as the L-function for the marked point process to determine the interaction between events belonging to different classes.

Using Monte Carlo simulations, we generated 999 random point processes with the same intensity function as the underlying point process within a circle of radius equals to 10km. In doing so, we have a null hypothesis (h_0) of completely spatial randomness from which we can extract critical values and compare with the original point process. In other words, we compare the estimated L-function with the simulated MC values to figure out if we can reject the null hypothesis of CSR and if the point process has a regular pattern or a clustered one. Figure A5 below shows the results of the L-function for homicides committed by civilians, homicides committed only by police officers, and lastly the combined of the two (marked point process).

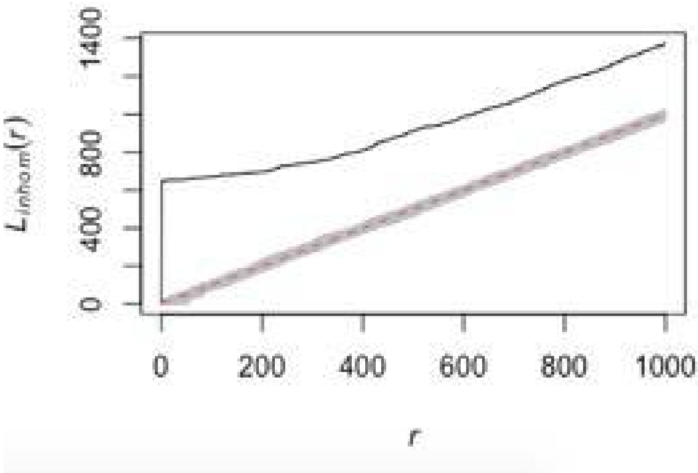
Figure A5: L- function



a) Homicide committed by police officers during daylight in days with good visibility



b) Homicide committed by police officers during nighttime in days with poor visibility



c) Homicide committed by police officers combining both point processes

Source: prepared by the authors.

By the results of the L-function presented in Figure A5, we can see that the L function is above the upper bound of the envelope in the three cases, suggesting a clustered pattern in the point processes.

It is important to emphasize that while the kernel estimators use the first-order intensity function to analyze the randomness of the point process, the L function incorporates the second-order intensity function in order to access the relation between events. In other words, the first-order intensity function is used to test if the point process is a homogeneous point process, while the latter tests are used to address micro-scale effects such as spatial autocorrelation through the covariance between events.