

Andre, Diego de Maria; Carvalho Júnior, José Raimundo de Araújo

Article

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Assessing the benefits of robbery reduction: The case of a large Brazilian city

Diego de Maria Andre^{a,c}, José Raimundo Carvalho^{b,c,*}

^a Federal University of Rio Grande do Norte (UFRN – PPECO), Av. Sen. Salgado Filho, 3000 Lagoa Nova, 59078-970 Natal, RN, Brazil

^b Federal University of Ceará (UFC – CAEN), Avenida da Universidade, 2762 2º andar Benfica, 60020-181 Fortaleza, CE, Brazil

^c Laboratório de Econometria – LECO/CAEN, Avenida da Universidade, 2762 2º andar Benfica, 60020-181 Fortaleza, CE, Brazil

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Abstract

We estimate willingness to pay (WTP) for a first-order stochastic reduction on the risk of robbery at a large city in Brazil. We develop a structural choice model that nests a process of contingent valuation among non-degenerate lotteries and estimate it by both maximum likelihood and geographically weighted regression (GWR) using a dataset from the city of Fortaleza that contains a precise measurement of individual's subjective probability of victimization among detailed socioeconomic measurement, willingness to pay, and police presence variables. Expected loss, gender, age, education, and perception of patrolling explain WTP. Our global model estimated a mean WTP of R\$ 19.23 (US\$ 10.33) per month. Our local model, estimated by GWR, suggests that there is a reasonable amount of spatial heterogeneity that follows the city's socioeconomic spatial distribution profile. Although the city's northwest periphery presents higher WTP, as long as we go inwards, there is plenty of heterogeneity on its spatial distribution. Our results support a theory of crime with an active role for victim's (costly) precautions influenced by socioeconomic spatial heterogeneity.

JEL classification: O18; Q51; C31

Keywords: Urban crime; Contingent valuation; Spatial effects

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1. Introduction

In recent years, Brazil has experienced a significant increase in the number of people who has been a victim of a crime against property. According to Arias et al. (2013), in 2011, Brazil had a robbery rate of 572.7 per 100,000 inhabitants, which place it among the three most dangerous countries in Latin America.¹ In the city of Fortaleza, the focus of this paper, the situation is even worse.

* Corresponding author.

E-mail address: josecarv@ufc.br (J.R. Carvalho).

¹ The worst two countries are Argentina (973.3) and Mexico (688) (Arias et al., 2013).

Fortaleza is the state capital of Ceará, located in Northeastern Brazil. The city has a population of about 2.5 million, and it is the fifth largest city in Brazil with an area of 313 km², boasting one of the highest demographic densities in the country (8001 per km²) (IBGE, 2012). In 2011, year of the collection of the data used in this paper, the robbery rate in Fortaleza was 1,355 per 100,000 inhabitants,² approximately 2.36 times greater than the average Brazilian rate.

Living in a city with a high rate of criminality can cause negative impacts not only on physical health but also on mental health. Some studies have found that mental health problems such as depression, anxiety, and post-traumatic stress disorder are highly related to exposure to non-lethal violence (Lopes et al., 2003; Vaughn et al., 2010; Andrade et al., 2012; Ribeiro et al., 2013; Fichera et al., 2014; Murray et al., 2018).

In addition to the adverse effects on health, fear of victimization makes people change the way they organize their life. According to Arias et al. (2013), in Brazil, 24.7% of individuals said they have reduced their leisure activities in the last 12 months due to the lack of security. Also, 16.8% of Brazilians avoided going to shopping places during the same period as a result of delinquency. People also invest more in insurance and private security. Brazilians spent with these two services, in 2015, up to 0.94% and 0.8% of the country's gross domestic product, respectively (SEAE, 2018).

Arias et al. (2013) state that the fear of victimization generates an impact on the behavior, limiting freedom and diminishing the quality of life. Therefore, it is primordial that the government implements public policies able to face criminality. However, these policies are expensive. Hence, before implementing new public policies, it is necessary to execute a benefit-cost analysis, especially in developing countries where governments face significant budgetary constraints (Quah, 2017).

Benefit-cost analysis is an economic exercise that identifies whether a project or policy is efficient (Whitehead and Blomquist, 2006). It requires that we place a monetary value on benefits generated by the program. One of the ways to estimate a monetary value of benefits is by means of a stated preference approach called contingent valuation method.

Contingent valuation has been used successfully to estimate the value of goods in areas such as environmental economics and health economics. However, in the economics of crime, few papers have applied that method so far.

Among studies that make use of contingent valuation, only Ludwig and Cook (2001), Cohen et al. (2004), Atkinson et al. (2005), and Soeiro and Teixeira (2010) considered non-degenerate lotteries, that is, lotteries that involve at least two different payoffs with positive probability. However, they stopped far from building an econometric model that incorporates the basic tenets of choice under risk.

Given the lack of a conceptual empirical strategy for contingent valuation among lotteries, and the incipient literature on willingness to pay for crime reduction policies, the objective of our paper is to build (and estimate) an econometric model capable of assessing willingness to pay for first-order stochastic reductions in the risk of robbery. Specifically, we seek to identify potential factors that may influence individuals' willingness to pay as well as to investigate if spatial effects play an important role in determining individuals' willingness to pay in a large and densely populated urban center in Brazil.

We believe to have succeeded in a satisfactory way. We made use of a unique geo-referenced sample of 4,030 households from the city of Fortaleza, CE (Brazil), which contains information on socioeconomic background, experience, expectation of victimization, and willingness to pay to reduce crimes (see Carvalho (2012)).

For the **global** model (i.e., without spatial effects), we found that variables such as *gender*, *age*, *marital status*, and *categorical subjective probability*, explain the decision between to pay or not a positive value to maintain a program that reduce crimes (selection equation), while variables such as *expected loss*, *gender*, *age*, *education*, and *perception of patrolling* explain differences about how much to pay (outcome equation).

As to the selection equation, the negative signs of variables *gender* and *age* mean that men and older people tend to refuse to pay any amount the program's maintenance. On the other hand, variables *marital status* and *categorical subjective probability* show positive signs, meaning that married people and those who believe they have a higher probability of being a victim of robbery tend to accept to pay to keep the program.

As to the outcome equation, the positive sign of variables *gender*, *education*, and *perception of patrolling* means that men, more educated people and those who have lower perception of police patrolling want to pay more for risk reductions. On the other hand, the negative sign of variable *age* means that older people tend to pay less to reduce crime compared to youngers. Finally, regarding variable *expected loss*, its positive sign indicates that an increase in income

² According to SSPDC-CE, in 2011, the number of robberies in Fortaleza was equal to 33,240.

or an increase in the difference of subjective probabilities of being robbed between *status quo* and the proposed new lottery or both, leads to higher values of willingness to pay to reduce the risk of being stolen.

We also estimated a monthly average willingness to pay of R\$ 19.23³ (US\$ 10.33) per household, a value of R\$ 3.98 (US\$ 2.13) greater than the estimated value from the nonparametric form. We also estimated the implicit value of a statistical robbery equal to R\$ 9861.61 (US\$ 5,301.94) per crime avoided. Both values are quite reasonable. Our proposed specification made possible to implicitly estimate the average cost of each robbery in the city of Fortaleza. This amount is approximately 3% of the average income or R\$ 44.66 (US\$ 24.01) per robbery.

Our **local** model reveals the full spatial heterogeneity present in the dataset. Through a geographically weighted regression, it is possible to allow the estimation of local parameters rather than global parameters (Fotheringham et al., 2003). Now, the main difference is the lack of one estimated parameter for each independent variable. Instead, for each independent variable, we have a (possibly) different parameter for each sampled point. Overall, the estimated spatial heterogeneity brings us both expected results and surprises. The estimate mapping for variables *gender*, *age* and *education* present a reasonable amount of spatial heterogeneity and, as expected, follow the very inertial city's socioeconomic spatial distribution profile. Given the geographically weighted regression, we apply Kriging techniques to calculate a surface of willingness to pay.

The image that emerges from such empirical exercise is not difficult to rationalize: age, income, and the spatial distribution of crime in the city have a relevant effect on Fortaleza's surface of willingness to pay. Although the city's peripheries present lower willingness to pay, as long as we go inwards, there is plenty of heterogeneity on the spatial distribution of willingness to pay for reductions on the prevalence of robbery. It is worth noting that the highest willingness does not come from the richest one, a fact that corroborates with a theory of crime with an active role for victim's (costly) precautions.

The rest of the paper is structured as follows. In Section 2, we present a brief review of the literature. Section 3 introduces the dataset and some descriptive statistics. Section 4 develops a simple structural model of contingent choice between risky lotteries and frames the resulting equation as a fully parametric econometric model. Notwithstanding that, we end up estimating our model by fully maximum likelihood. Mathematical details and hypothesis appear in the Appendix. In order to introduce our spatial effects, Section 5 deals with geographically weighted regression and how to manage that in our context. We call such model "**local**" to contrast with the previous one that neglects spatial effects. Section 6 presents results as well as their interpretations. Finally, Section 7 elaborates more on results and proposes futures improvements.

2. Benefit-cost analysis and contingent valuation

Benefit-cost analysis identifies whether a government project or policy is efficient by estimating and examining the present value of the net benefits (the difference between benefits and costs) of a project (Whitehead and Blomquist, 2006). A positive value indicates that the project generates more gain than losses and the project is more efficient than the status quo (Whitehead and Blomquist, 2006).

This process requires that we place a monetary value on the benefits generated by the program. As Whitehead and Blomquist (2006) state, the social impact of a project or public policy includes market and non-market dimensions. Market impacts can be estimated using changes in market prices and quantities. Non-market impacts, on the other hand, deserves special attention.

According to Whitehead and Blomquist (2006), the monetary value of non-market impacts can be estimated using revealed preference or stated preference approaches. The main difference between them is that the former uses data from past individual behavior to infer non-market impacts, while the latter uses hypothetical questions about future behavior. Our choice here is for stated preference approaches.

A stated preference approach consists in constructing a hypothetical market, as realistic and structured as possible, such that researchers can extract the maximum willingness to pay of individuals for those goods. The method uses information on how people say they would behave given certain hypothetical situations, contingent on being in the real one (Whitehead and Blomquist, 2006).

³ In December 29th, 2011, US\$ 1 = R\$ 1.86.

Bowen (1943) and Ciriacy-Wantrup (1947) were pioneers to propose the use of public opinion surveys specially developed for the valuation of *social goods* or *collective goods* (Carson and Hanemann, 2005). These authors believed that voting would be the closest substitute to consumer choice, so they considered that public opinion surveys would be valid instruments for valuation of these goods (Hoyos and Mariel, 2010; Carson and Hanemann, 2005).

Although the principal objective of contingent valuation is to measure the monetary value of a specific good for an individual (Carson and Hanemann, 2005), there is a much more powerful insight on top of it: welfare analysis. According to Hoyos and Mariel (2010), it is also possible to directly obtain a monetary measure (Hicksian) of welfare associated with a discrete change in the provision of an environmental good, either by the substitution of one good for another or by the marginal substitution of different attributes of an existing good.

To understand the measurement of this value by agents, we follow Whitehead and Blomquist (2006) and Carson and Hanemann (2005). Define a utility function that, for simplicity, only depends on a good x and a contingent good q , given by $u(x, q)$. Thus, assuming that good q is desirable, and that q^0 is the state in which the consumer does not have the good and q^1 is the state in which the consumer has access to the good, the consumer will pay for the good q if, and only if, $u^1(x, q^1) > u^0(x, q^0)$.

Consumers will maximize their utility function $u(x, q)$ subject to a budget constraint given by $y = px + tq$, where y is the consumer's income, p is the price of good x and t is the price of contingent good q , to define the optimal level of consumption of goods x and q . From this, we find the indirect utility function, denoted by $v(p, t, y)$, whose usual properties regarding p and y are satisfied.

On the other hand, solving the problem of minimizing costs, subject to the constraint level of utility in state q^0 , generates an expenditure function given by $e(p, t, u)$, (see Mas-Colell et al. (1995)). According to Carson and Hanemann (2005), the value for the individual, in monetary terms, of the increment in utility caused by the change of state from q^0 to q^1 can be represented by two Hicksian measures: the compensatory variation and the equivalent variation (Mas-Colell et al., 1995). Formally, those measures are solutions to the following equations:

$$v^1(p, t, y - C) = v^0(p, t^0, y) \quad (1)$$

$$v^1(p, t, y) = v^0(p, t^0, y + E), \quad \text{where } t^0 < +\infty \quad (2)$$

Based on these two concepts, one can define willingness to pay in two different ways: (i) as the difference between expenditure functions in the situation without contingent good q and with contingent good q , and, (ii) as the monetary value that leaves the consumer indifferent between the *status quo* and the state where provision of contingent good q is increased. Following Carson and Hanemann (2005), it is possible to define willingness to pay's function as a function of initial value q^0 , terminal value, q^1 , and values of p and y in which the changes in q occur.

However, a common assumption for both $C(q^0, q^1, p, y)$ or $E(q^0, q^1, p, y)$ is the fact that what is measured is a discrete change between two deterministic states of nature with degenerate distribution, i.e., from initial value q^0 (*status quo*) with $Prob(q^0) = 1$ up to the terminal value, q^1 with $Prob(q^1) = 1$. The more general and interesting case of measuring willingness to pay for changes between (non-degenerate) lotteries of states of nature are still lacking a complete approach in the literature, although Cameron et al. (2010) and Cameron and DeShazo (2013) are notably exceptions.

Although the scope of applicability of contingent valuation methods has grown considerably, it has not thoroughly reached many areas traditionally approached by economists. A notable example is the Economics of Crime. Since problems of measurement, externalities, and difficulties in assessing costs plague this area, it appears to us that underutilization of contingent valuation methods is hard to understand.

Ludwig and Cook (2001) estimate the benefits of reducing crime using contingent valuation methods. They focused on gun violence, in a national survey in the United States. Using a parametric form, they estimated a value of US\$ 24.5 billion as the worth for American society for a 30% reduction in gun violence or US\$1.2 million per injury avoided. Still in the United States, Cohen et al. (2004) using a nationally representative sample of 1300 United States residents, claimed that the representative American household would be willing to pay between US\$ 100 and US\$ 150 per year for programs that reduced specific crimes by 10% in their communities. Cohen et al. (2004) analyzed five types of crimes: burglary, serious assault, armed robbery, rape or sexual assault and murder.

In the United Kingdom, Atkinson et al. (2005), using a dataset with 807 observation, estimated the costs of three violent crimes: common assault (no injury), other wounding (mild injury) and grave wounding (serious injury). At the interview, interviewers informed the interviewed that the probability of being victims of each crime was 4% for

common assault and 1% for both other wounding and grave wounding. Then each respondent was asked to express his willingness to pay to reduce their chance of being victims of this offense by 50% over the next 12 months. The estimated values for willingness to pay were £ 105.63, £ 154.54 and £ 178.33 for common assault, other wounding and grave wounding, respectively.

In Portugal, [Soeiro and Teixeira \(2010\)](#) studied the determinants of higher education students' willingness to pay for reducing the risk of being victims of violent crimes. They conducted an online survey with students from the University of Porto, which had 1,122 respondents. Through a parametric approach, they modeled willingness to pay as a function of demographic factors (age and gender), family-related factors (income, dimension, dependents), degree (undergraduate, master, Ph.D.) and field of study (economics, arts, among others), crime-related factors (crime victim, crime time, physical injuries, psychological damages, fear of crime), averting behavior (locking doors), payment vehicle and policy. They found that variables such as age and family members had negative impacts in willingness to pay, whereas variables such as gender, fear of crime, locking doors and payment vehicle had positive effects on willingness to pay.

In Brazil, [Araújo and Ramos \(2009\)](#) used contingent valuation to estimate the loss of welfare associated with insecurity, through willingness to pay. They used a sample of 400 observations from the habitats of the city of *João Pessoa (PB)*. Each sample unit answered how much he or she would be willing to pay for a bundle of public security services, which includes: fixed police posts equipped with adequate weaponry, vehicles equipped for better care and effective police action, trained officers integrated with the community, day-and-night patrols, and conduction of educational programs to prevent violence and crime.

They found that besides being a common good, public security is also a normal good, that is, its demand increases when income increases. They also found that the estimated cost of insecurity in *João Pessoa* varies between R\$ 6,524,727.01, considering the most conservative estimate, and R\$ 104,864,863.52 for the highest value.

Although those authors propose valuations between non-degenerate lotteries, they stopped far from building an econometric model that incorporates the basic tenets of choice under risk. So, as one of the objectives of this study, we build an econometric model capable of assessing willingness to pay for first-order stochastic reductions in the risk of robbery, which we present in the Appendix. In the next section, we show the dataset used in this study.

3. Dataset

Our dataset is a household survey on socio-economic conditions and safety carried out in 2012 by [Carvalho \(2012\)](#) with residents of the city of Fortaleza. The sampling plan took three stages which guarantees representativeness. At the first stage, the total sample was stratified among all the districts (*bairros*) of Fortaleza, based on the number of residents of each neighborhood ([IBGE, 2012](#)). At the second stage, census tracts have been selected within each district, using the “probability proportional to size” method. At the third stage, selection of respondents followed a “proportional quotas” approach, according to gender, age, schooling, and family income ([Carvalho, 2012](#)).

A total of 4,030 households were sampled along all 119 *bairros* from Fortaleza (Brazil), during the months of October 2011 to January 2012. [Fig. 1](#) shows the spatial distribution of the sample. Besides information about socioeconomic background, experience, and expectation of victimization, respondents expressed their willingness to pay to reduce certain types of crimes.

The section about contingent valuation presents respondents with a fictional scenario where a program to fight against criminality is proposed, more specifically to fight robberies. After this, respondents received information that the program will reduce robberies by 50%. However, to maintain this program, it was necessary to fund it via fictitious future taxes. Then, interviewers asked respondents if they were willing to pay a monthly fee to maintain that crime prevention program, and if so, how much they would be willing to pay. The exact question-wording were:

- *Introductory Remark: Now I would like to know how much you are willing to spend to reduce certain crimes in your town. In each case, I will ask you to answer whether you would vote “yes” or “no” for a bill that would require from you and from each household in your community a payment to prevent certain crimes. Remember that the money you agree to spend to prevent crimes is the same that you could use to buy food, clothes or other needs to you and to your family.*

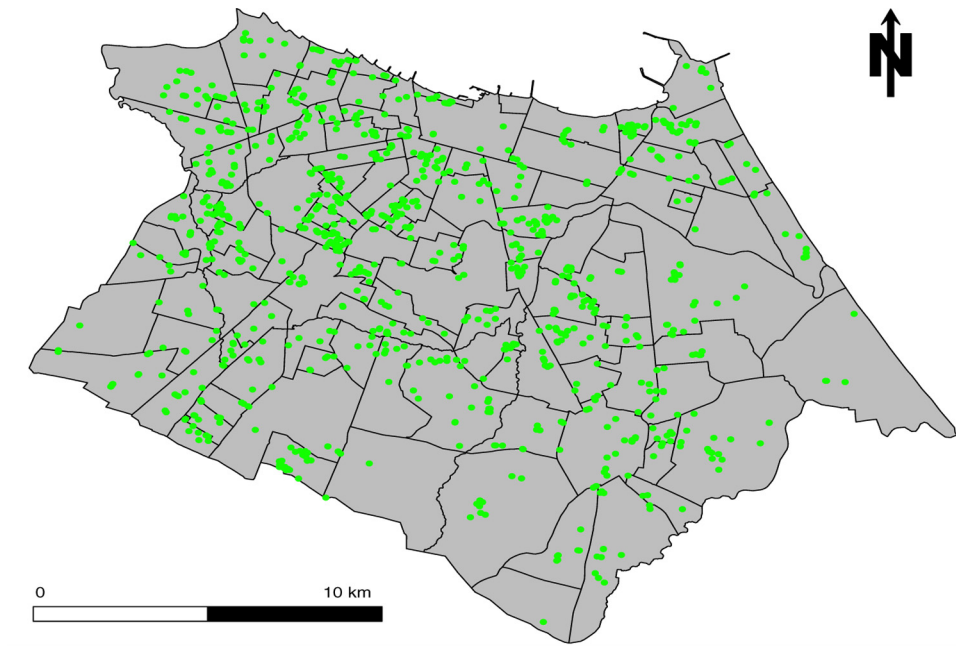


Fig. 1. Spatial distribution of households interviewed in Fortaleza (Brazil).

Table 1
Variables' descriptions.

Variable	Description
Gender	1 if male; 0 if female
Age	Years
Income	R\$
Education	(1) No education; (2) Incomplete fundamental school; (3) Complete fundamental school; (4) Incomplete high school; (5) Complete high school; (6) Incomplete undergraduate degree; (7) Complete undergraduate degree; (8) Graduate Program
Victim of robbery	1 if you've been the victim of robbery; 0 otherwise
Subject prob.	Subjective probability of being a victim of a robbery in the next 12 months $\in (0,1)$
Categorical subjective probability	(1) Not likely to occur; (2) Very little probability to occur; (3) Unlikely to occur; (4) Moderate probability to occur; (5) Very likely to occur; (6) Very great probability to occur; (7) Certainly to occur
Perception of patrolling	(1) Always; (2) Often; (3) Sometimes; (4) Rarely; (5) Never
Marital status	1 if married or living together; 0 otherwise
Expected loss	Income multiplied by the subjective probability of being a victim of a robbery
Willingness to pay	R\$/month

Source: Elaborated by the authors.

- Question: *Q105 Now forget about this program that was able to reduce homicides and think about a new one. Let's suppose a new government program funded by the population of Fortaleza managed to cut the occurrence of personal robbery in the city in half. Would you be willing to pay a monthly amount to keep this program for crime prevention?*

Table 1 shows variables related to socioeconomic profiles, perceptions of security, experiences of victimization, and the expected loss of sampled participants.

Table 2
Sample description – total.

Variable	Mean	Std. dev.	Min	Median	Max	NA	N
Gender	0.44	0.49	0	0	1	0	3778
Age	39.45	16.83	16	37	94	80	3698
Income	1489	1525	272	817	10,900	137	3641
Education	3.55	1.64	1	3	8	0	3778
Victim of robbery	0.23	0.42	0	0	1	1	3777
Subject prob.	0.49	0.29	0	0.50	1	532	3246
Categorical subjective probability	4.20	1.74	1	5	7	31	3747
Perception of patrolling	2.05	1.21	1	1	5	10	3768
Marital status	0.52	0.49	0	1	1	0	3778
Expected loss	191.14	250.94	0	109	2588.75	640	3138
Willingness to pay	17.99	26.82	1	10	151	2146	1632

Source: Elaborated by the authors.

Table 2 brings descriptive statistics for those variables. It shows that 44.71% of respondents are men and 52.06% are married.⁴ Overall respondents are 39.45 years old, with complete fundamental school level. As to income, the average level is R\$ 1489.80 (US\$ 800.96) per month, but about 50% of respondents earn R\$ 817.50 (US\$ 439.51) or less.⁵

As to victimization and perception of security, 23.27% of respondents were robbery victims at least once in the last five years. Regarding the perception of security, on average, respondents considered that their probability of being robbed in the next 12 months is moderate (49.18% in numerical probability), although the perception of patrolling is frequent (mean 2.05). They also informed that their expected loss in a robbery is R\$ 191.14 (US\$ 102.76).

Out of the 3778 respondents shown in Table 2, 1702 (45.05%) answered that they are willing to pay a monthly fee to fund the program to combat robberies, while 2076 (54.95%) of them answered they would not pay any amount.⁶ In the contingent valuation literature, this second group is called *protesters*.

These people refuse to pay for a good either because they think they already pay many taxes or, in the case of public goods, because the provision of such goods is a responsibility of the government, or just because they think it is an obligation that other groups should pay for it.⁷ However, it is possible that someone reports a true zero value or merely cannot afford to pay for such amount. Notwithstanding that, we will not enter into that debate,⁸ and we merely characterize them as *protesters*.

Table 3 depicts the *protesters*' group. 50.48% of them are men and 51.83% are married, with an average age of 41.42 years old and with complete fundamental school level. In this group, the average income is R\$ 1488.90 (US\$ 800.48), but 50% of them earned R\$ 817.50 (US\$ 439.51) or less. As to the expectations of victimization and perception of security, 22.74% of them suffered at least one robbery in the last five years, and they consider that their probability of being robbed in the next 12 month is moderate (48.47% in numerical probability), even though the perception of patrolling is frequent. They also report a mean expected loss of R\$ 191.01 (US\$ 102.69).

In the contingent valuation literature, the standard procedure for dealing with this group is to remove them from the sample and proceed to the estimation of maximum willingness to pay (Strazzera et al., 2003). However, Strazzera et al. (2003) states that this procedure is valid only when both groups are similar. If this is not the case, selection bias might be a concern.

We compared the empirical distributions for both: *protesters* and those who are willing to pay. Both groups appear to be similar (see Tables 3 and 4), respectively).

⁴ Out of 4030 observations in the initial sample, we removed 252 observations due to lack of information about participation in the program and due to the difficulty in georeferencing respondents' addresses.

⁵ The minimum wage in Brazil at the time of the survey was R\$ 545.00 (US\$ 293.01).

⁶ The fact that the number of people who are not willing to pay to keep the program is high is consistent with other studies about contingent valuation, such as Atkinson et al. (2005) and Araújo and Ramos (2009), which had a rate of 34.57% and 48.5%, respectively.

⁷ We also consider the fact that individuals do not report their willingness to pay for fear that, once answered a value, the research can be used to make them pay the reported amount.

⁸ For details, see Jorgensen et al. (1999).

Table 3
Sample description – protesters.

Variable	Mean	Std. dev.	Min	Median	Max	NA	N
Gender	0.50	0.50	0	1	1	0	2076
Age	41.42	17.47	16	39	93	26	2050
Income	1488.90	1553.82	272.50	817.50	10,900.00	84	1992
Education	3.51	1.68	1	3	8	0	2076
Victim of robbery	0.22	0.42	0	0	1	0	2076
Subject prob.	0.48	0.29	0	0.50	1	302	1774
Categorical subjective probability	4.16	1.815	1	5	7	22	2054
Perception of patrolling	2.07	1.22	1	2	5	6	2070
Marital status	0.51	0.49	0	1	1	0	2076
Expected loss	192.01	263.25	0	109	2588.75	366	1710

Source: Elaborated by the authors.

Table 4
Sample description – willing to pay.

Variable	Mean	Std. dev.	Min	Median	Max	NA	N
Gender	0.37	0.48	0	0	1	0	1702
Age	37.01	15.67	16	34	94	54	1648
Income	1490.90	1490.44	272.50	817.50	10,900.00	53	1649
Education	3.60	1.59	1	4	8	0	1702
Victim of robbery	0.23	0.42	0	0	1	1	1701
Subject prob.	0.50	0.30	0.010	0.50	1	230	1472
Categorical subjective probability	4.26	1.65	1	5	7	9	1693
Perception of patrolling	2.02	1.19	1	1	5	4	1698
Marital status	0.52	0.49	0	1	1	0	1702
Expected loss	190.09	235.45	0.68	122.62	2180	274	1428
Willingness to pay	17.99	26.82	1	10	151	70	1632

Source: Elaborated by the authors.

We also run the Kolmogorov–Smirnov test and plot the empirical CDF for both groups. We present these results in Appendix 2, which indicates that selection bias will not affect the estimates of the maximum willingness to pay using only the second group (Strazzera et al., 2003), as long as observed variables define the selection.

However, we choose to estimate our (non-spatial) model with the due selection bias correction.⁹ Due to challenging computational complications out of the scope of our present investigation we estimated our spatial model without correction for selection bias, excluding *protesters* and keeping only those with a strict positive willingness to pay.

Table 5 shows the frequency distribution of willingness to pay for 1,632 respondents who inform a positive value of willingness to pay. Columns *cumulative frequency* and *survival probability* indicate, respectively, the absolute and the percentage of the people who are willing to pay less or equal the indicated value. This means that 998 people are willing to pay up to R\$ 10 for the maintenance of the combating robbery crimes program.

From this empirical distribution of willingness to pay, we estimated, nonparametrically, maximum willingness to pay.¹⁰ We estimated a value of R\$ 15.25 (US\$ 8.20) as the average monthly value or R\$ 183 (US\$ 98.38) per year, as the value that each household would be willing to contribute to reduce the number of robberies in the city of Fortaleza by 50% (Fig. 2).

Thus, multiplying this value by the total amount of households in Fortaleza, that according to IBGE (2012) is 709,952 households, we estimated a total value of willingness to pay approximately equal to R\$ 130 (US\$ 69.89) million per year. Finally, considering that in 2011 the number of occurrences of robberies in the city of Fortaleza was

⁹ We thank an anonymous referee for pointing out this.

¹⁰ We consider only who answered that would be willing to pay at least R\$ 1.00 and up to R\$ 100.00 per month.

Table 5
Willingness to pay frequency distribution.

WTP	Frequency	Cumulative frequency	Survival probability
1	212	1632	1.00
5	427	1420	0.87
10	458	993	0.60
15	159	535	0.32
25	171	376	0.23
50	122	205	0.12
75	12	83	0.05
100	38	71	0.04
150	8	33	0.02
+150	25	25	0.01

Source: Elaborated by the authors.

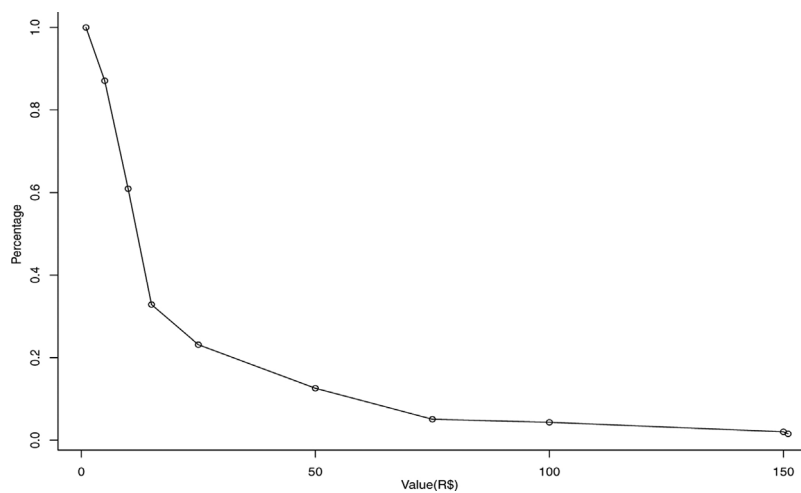


Fig. 2. Survival function.

equal to 33.240,¹¹ we have that the implicit value of a statistical robbery is equal to R\$ 7821.90 (US\$ 4205.32), that is the cost of a robbery to society.¹²

However, this nonparametric estimation is not the ideal procedure to estimate maximum willingness to pay, since we expect that individual characteristics influence the amount individuals are willing to pay. So, in the next section, a parametric model to estimate the maximum willingness to pay for the maintenance of the program to reduce robberies will be presented.

4. A global econometric model

Given the significant amount of *protesters* in our sample (54.86%), it seems reasonable to apply some estimation method that deals with selection bias. We applied a Heckman-type approach. At the first stage, the so-called participation equation, individuals choose to pay (or not) any amount to keep the program of crime prevention.

$$y_1 = \begin{cases} 1 & \text{if } y_1^* > 0 \\ 0 & \text{if } y_1^* \leq 0 \end{cases} \quad (3)$$

¹¹ Considering only robberies informed to the public security authorities. Source: SSPDC-CE.

¹² To obtain this value, just divide R\$ 130 million by 16,620, the last one being the number of robberies avoided.

At the second stage, after he/she decided to contribute, he/she decides how much to pay. The outcome equation is:

$$y_2 = \begin{cases} y_2^* & \text{if } y_1^* > 0 \\ - & \text{if } y_1^* \leq 0 \end{cases} \quad (4)$$

This model specifies that y_2 is observed when $y_1^* > 0$, whereas y_2 need not take on any meaningful value when $y_1^* \leq 0$ (Cameron and Trivedi, 2005). For the participation equation, we assume for simplicity a linear model for the latent variable y_1^* .

$$y_1^* = Z\beta + u \quad (5)$$

where Z is a vector of observable individual characteristics and u is an error term.

In the outcome equation, given the nature of our data, we are not able to observe the real value of y_2 itself, but only in which interval it lies. Cameron and Huppert (1989) propose that contingent valuation datasets obtained through payment cards' method can be analyzed parametrically through maximum likelihood models with data in intervals. They suggest that when an agent chooses a value in the payment card, say α_{ui} , the true value of the agent's willingness to pay is greater than or equal to this value, but less than the next card value, say α_{u+1i} . Thus, we only know that $y_2 \in [\alpha_{ui}, \alpha_{u+1i})$. Hence, we have (Henningsen et al., 2017):

$$y_2 = \begin{cases} - & \text{if } y_1 = 0 \\ 1 & \text{if } \alpha_1 < s^* \leq \alpha_2 \text{ and } y_1 = 1 \\ 2 & \text{if } \alpha_2 < s^* \leq \alpha_3 \text{ and } y_1 = 1 \\ \vdots & \\ M & \text{if } \alpha_M < s^* \leq \alpha_{M+1} \text{ and } y_1 = 1 \end{cases} \quad (6)$$

For the latent variable s^* , we built a contingent valuation model to assess willingness to pay for a first-order stochastic improvement on the odds of being robbed in the city, when subjective expectations about the risk are available. We present the details of this model in Appendix 1. Eq. (7) shows the final expression to maximum willingness to pay:

$$\ln(s^*) = X\varphi + \varrho EL + \epsilon \quad (7)$$

where X is a vector of observable individual characteristics, EL is the amount of money that an individual expect loss in a robbery, which is defined as the product of *per capita* income by the difference between the subjective probability of being robbed in the *status quo* and the new situation, and ϵ is an error term.

We can estimate this model by maximum likelihood given the additional assumption that the correlated errors are joint normally distributed and homoscedastic, with (Henningsen et al., 2017):

$$\begin{pmatrix} u \\ \epsilon \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix} \right] \quad (8)$$

Before we proceed, it is worth noting that models that incorporate willingness to pay for first-order stochastic dominance improvements on risks are a somewhat new endeavor.

In fact, as the best of our knowledge, there are only three studies that build around this topic, say, Cameron and Englin (1997), Cameron et al. (2010) and Cameron and DeShazo (2013), although they did not deal with first-order stochastic policies. Their approach is different from ours, and none model a set up where the proposed change to the *status quo* is a new lottery that first-order (stochastic) dominates the original risk state. Last, but not least, it is important to stress that individual's subjective expectations play a crucial role in our modeling strategy.

Therefore, following [Henningsson et al. \(2017\)](#), the probability that WTP lies in the m th interval is:

$$\begin{aligned}
 P(y_1 = 1 \ \& \ y_2 = m) &= P(y_1^* > 0 \ \& \ \alpha_m < s^* \leq \alpha_{m+1}) \\
 &= P(y_1^* > 0 \ \& \ \log(\alpha_m) < \log(s^*) \leq \log(\alpha_{m+1})) \\
 &= P(Z\beta + u > 0 \ \& \ \log(\alpha_m) < X\varphi + \varrho EL + \epsilon \leq \log(\alpha_{m+1})) \\
 &= P(u > -Z\beta \ \& \ \log(\alpha_m) - X\varphi - \varrho EL < \epsilon \leq \log(\alpha_{m+1}) - X\varphi - \varrho EL)
 \end{aligned} \tag{9}$$

Thus, the log-likelihood contribution of the i th observation is ([Henningsson et al., 2017](#)):

$$\begin{aligned}
 l_i = (1 - y_{1i}) \ln [\Phi(-Z\beta)] + \sum_{m=1}^M y_{1i}(y_{2i} = m) \ln \left[\Phi_2 \left(\frac{\log(\alpha_{m+1}) - X\varphi - \varrho EL}{\sigma}, Z\beta, -\rho \right) \right. \\
 \left. - \Phi_2 \left(\frac{\log(\alpha_m) - X\varphi - \varrho EL}{\sigma}, Z\beta, -\rho \right) \right]
 \end{aligned} \tag{10}$$

As [Cameron and Trivedi \(2005\)](#) state, the model given by Eq. (10) is theoretically identified without any restriction on regressors. The model is close to unidentified, however, if Z and X contain exactly the same regressors. The reason for this is that the inverse Mills ratio term $\lambda(z)$, although being a nonlinear function, it is often well-approximated by a linear function. As a result, if Z and X are equals, then $\lambda(z)$ can be highly correlated with X , which leads us to face multicollinearity problems.

Therefore, for practical purposes, estimation of sample selection models require that at least one regressor in Z be excluded from X . In other words, we need a variable that affects the decision to pay (or not) any amount to keep the program of crime prevention but has no direct impact on how much to pay.¹³

From the maximization of (10), we find the optimal values of β , φ , ϱ , σ and ρ , with values of β and φ showing, respectively, the impact of individual characteristics on the choice if he or she wants to pay any amount to maintain the program of crime prevention and how much he or she pays. We also have $\hat{\varrho}$ as an estimate of the average amount of money taken in a robbery. From these estimated values, we can estimate the conditional mean and the conditional median WTP (y_2), as shown below:

$$E(y_2|X, Z, y_1^* > 0) = \exp(X\varphi + \varrho EL) \exp(\sigma^2/2) + \rho\sigma\lambda(Z\beta) \tag{11}$$

$$\text{medianWTP}(y_2|X, Z, y_1^* > 0) = \exp(X\varphi + \varrho EL) + \rho\sigma\lambda(Z\beta) \tag{12}$$

where $\lambda(z) = \phi(z)/\Phi(z)$ is the inverse Mills ratio.

These two measures provide what we call a global value for WTP. However, we expect spatial heterogeneity plays an important role to explain the relationship between the choice of how much the agent wants to pay and his characteristics. This means that the values for φ and ϱ can be different, which would make individual WTP values differ all over the city.

A plausible explanation for this would be that individuals in different neighborhoods meet different levels of criminality, whether observed or not by police authorities,¹⁴ which would lead their willingness to pay to be different. Also, the spread of information about crimes throughout the urban fabric is not understood so far.

Hence, to handle this issue of spatial heterogeneity, we use the geographically weighted regression technique (GWR) to estimate a local WTP in such a way that it will be possible to identify in which regions the WTP will assume higher values. Next section presents the GWR model.

5. A “local” econometric model

According to [Almeida \(2012\)](#), if one analyzes only the average or global response of a phenomenon it may not be useful or convenient. This is so because socioeconomic phenomena are likely to be different in different regions.

¹³ We thank an anonymous referee for pointing out this.

¹⁴ The security agencies only have access to the criminality level in an area from the time the citizen registers the event of a crime on, which does not always happen.

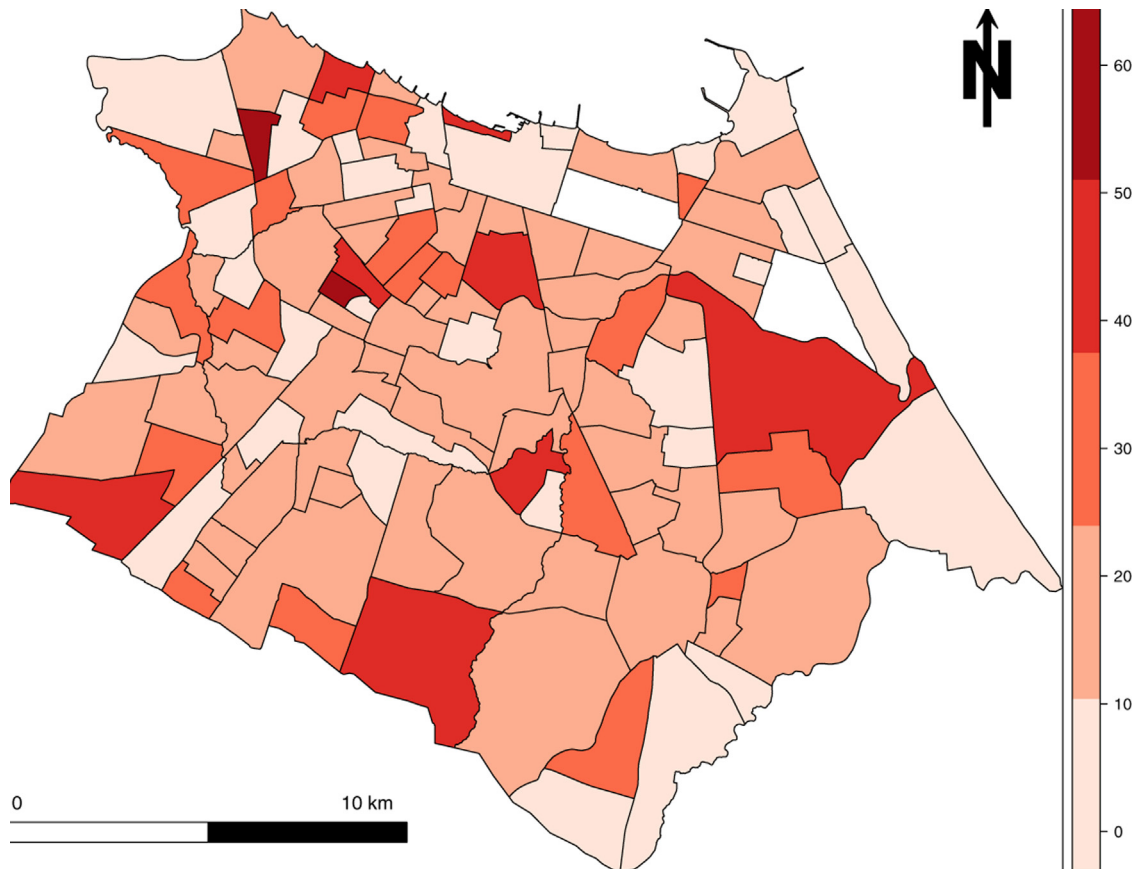


Fig. 3. Spatial distributions of willingness to pay by districts.

Fotheringham et al. (2003) refer to this situation as spatial non-stationarity and claim that a global statistic does not represent well any relationship that is non-stationary over space. Indeed, this global value may be very misleading locally.

Fotheringham et al. (2003) claim that there are several reasons to expect that a relationship varies over space. Among possible explanations, we can cite sample variation, misspecification and, most importantly, there might be relationships which are intrinsically different across regions. In the last case, there can be spatial variations in peoples' attitudes or preferences, or there can be different administrative, political or other contextual issues that produce different responses to the same stimuli over space.

It is a stylized fact that crime distribution is heterogeneous across urban space. In large cities, like Fortaleza (Brazil), robberies are concentrated in wealthier areas in the city, leading to the formation of crime clusters in these areas. Due to this heterogeneous distribution, we expect that individuals' reactions to crime are also heterogeneous. Indeed, Fig. 3 depicts the average willingness to pay for each *bairro* in our sample: spatial variation is clear.

We expect that individuals who live in a region with high rates of criminality have a different behavior *vis a vis* someone who lives in a low crime-prone region. Thus, unlike classical models of spatial dependence, here we do not expect that individuals can influence each other's willingness to pay, but we expect that everyone has a different set of factors affecting his or her willingness to pay. Thus, the same variable can have different effects on willingness to pay for individual i and individual j . In this sense, a local model is necessary to estimate this relationship.

Geographically weighted regression (GWR) is a method that extends the traditional regression framework by allowing estimation of local parameters rather than global parameters (Fotheringham et al., 2003). This method generates a sequence of regressions estimated for each region, using subsamples from the data, weighted by distance (Almeida, 2012). We create these subsamples from the *regression point*, that is the reference point for the parameters' estima-

tion for region i . We weight each observation belonging to the sample according to its distance to this point. Closer observations have a higher weight, while farther observations have a lower weight (Almeida, 2012).

The spatial kernel function is responsible for the calculation of the weights used for creating these subsamples. Almeida (2012) states that the kernel function is a real, continuous and symmetric function which integral sums one, like a probability density function. This function uses the distance (d_{ij}) between two points and a parameter of bandwidth (b) to determine a weight (w_{ij}) between these two regions, which is inversely related to geographic distance.

Fotheringham et al. (2003) classify the spatial kernel functions in two groups: fixed kernels and the adaptive kernels.¹⁵ In the fixed case, only one bandwidth (b) is chosen for every *regression point*, whereas in the adaptive case, one bandwidth (b_i) is chosen for each *regression point*, such that each subsample has the same proportion of the data. In our study, we use the adaptive Gaussian kernel, defined by Eq. (13):

$$w_{ij} = \begin{cases} \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b_i}\right)^2\right), & \text{if } d_{ij} < b_i \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Due to problems mentioned earlier, the choice of the bandwidth must consider the trade-off between bias and efficiency. To this end and to avoid arbitrary choices, the bandwidth is estimated using the data (Almeida, 2012). There are several techniques¹⁶ used to determine the optimal value of the bandwidth. In this paper, we use the cross-validation technique. It consists of minimizing the following function, represented by Eq. (14):

$$CVT = \sum_{i=1}^n (y_i - \hat{y}_{\neq i}(b))^2 \quad (14)$$

where y_i is the dependent variable, n is the number of observations, b is the bandwidth and $\hat{y}_{\neq i}(b)$ is the fitted value of y_i using a bandwidth of b with the observations for point i omitted from the calibration process (Almeida, 2012). Fotheringham et al. (2003) affirm that this approach has the desirable property of countering the wrap-around effect since when b becomes very small, the model is calibrated only on samples near to i and not at i itself.

After obtaining these weights generated by the kernel function, it is possible to get the local spatial weighting diagonal matrix:

$$W(i) = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix} \quad (15)$$

where w_{in} is the weight attributed to point n in the model calibration in *regression point* i , obtained by means of the spatial kernel function.

Returning to discussions about the *regression points*, Fotheringham et al. (2003) affirm that there is no reason that i has to be the location of a data point, that is, the *regression point* i can be observed or not, being any point in space. In our study, we opted to make our *regression point* coincide with our data points. Thus, the location of a *regression point* i is the coordinates of the interviewed household.

¹⁵ In the fixed kernels, bandwidth (b) is fixed, which may lead to problems of bias and efficiency. With a fixed bandwidth, the number of observations in each subsample may vary substantially. In regions where data are dense, the kernels are larger than they need to be and hence using information in excess, turning estimates biased. On the other hand, in regions where data is scarce, the kernels are smaller than they need to be to estimate the parameters' reliably. Adaptive kernels reduce both problems by making bandwidth (b) greater or smaller depending on data density in the area. For other types of kernel functions, see, among others, Fotheringham et al. (2003) and Almeida (2012).

¹⁶ For more details, see Fotheringham et al. (2003).

Thus, from the model shown in Eq. (7), we can specify our local model by the following weighted maximum likelihood function, represented by Eq. (16):

$$\log L_i = \sum_{j=1}^n w_{ij} \log \left[\Phi \left(\frac{\log(\alpha_{m+1j}) - X\varphi - \varrho EL}{\sigma} \right) - \Phi \left(\frac{\log(\alpha_{mj}) - X\varphi - \varrho EL}{\sigma} \right) \right] \quad (16)$$

where subscript i means that we have one equation for each *regression point*. From this equation, are estimated the following set of parameters $\{\varphi_i, \varrho_i, \sigma_i\}$ for each of the 1045 points where we had completed observations for all variables. Next section presents the results of the estimation for both global and local models.

6. Results

6.1. Results from the global model

Before we present and discuss our results, it is necessary to discuss our choices of “exclusion restrictions”. We dropped two variables: marital status and categorical subjective probability.¹⁷

As to variable *marital status*, we expect that married people have a greater sense of protection than single people. For example, Rader (2009) quote that married men demonstrate a heightened sense of personal fear and fear for spouses due to a new sense of “responsibility” for spousal safety and protection. This is what Warr and Ellison (2000) called *altruistic fear*, that is, fear for others. Therefore, we expect this variable to have a positive effect on the decision between pay or not to keep the program, but no effect on how much to pay.

As to variable *categorical subjective probability*, we expect that the higher is the subjective probability of being a victim of a robbery, the higher is the probability of acceptancing to pay to keep the program. However, we expect this variable to have no impact on the decision on how much to pay. We believe that expected loss is a more appropriate variable to explain the decision on how much to pay. That said, we can now discuss our estimates.

Table 6 shows results for the global model¹⁸ represented by Eq. (10). In the selection equation, only parameters estimates related to *gender*, *age*, *marital status*, and *categorical subjective probability* are statistically significant. the negative signs of estimates for *gender* and *age* indicate that males and older people are less inclined to pay any amount to the proposed new lottery of crime prevention program.

On the other hand, positive signs of estimates of variables *marital status* and *categorical subjective probability* mean that married people and people who believe that their probability of being a victim of a robbery is high are more inclined to pay some amount to crime prevention program.

In the outcome equation, all estimates are statistically significant, except for variable *victim of robbery*. Again, variable *age* shows negative signs, indicating that older people tend to pay less to reduce crime than young people. The positive signs of variables *gender* and *education* mean that men and more educated people tend to pay more to reduce the risk of being robbed. Finally, as we measured the variable *perception of patrolling* in decreasing order, its positive sign means that the lower is the perception of patrolling, the higher is the willingness to pay to reduce the number of robberies.

Variable *expected loss* deserves special attention. First, remember that $EL_i = Pr_{R|X}^{i,0}(r = 1|X) - Pr_{R|X}^{i,1}(r = 1|X)$ (see Appendix 1). Second, we have assumed Hypothesis 9, $E(MIX) = \tau Y$, i.e., the expected value of the robbery is proportional to the individual household’s *per capita* income. So, the coefficient associated with EL , ϱ , measures the fraction of the expected income lost conditional on the occurrence of a robbery.

The positive sign of this parameter estimate shows that the higher is the income or the difference of subjective probabilities of being robbed between *status quo* and the proposed new lottery, or both, the higher is the willingness to pay to reduce the risk. On the other hand, when the estimate of ϱ is multiplied by s^{max} , we have the fraction, on average, of the income robbed in each robbery. This value is equal to 0.03. So, in each robbery, approximately 3% of the income is lost. Multiplying this value by the average income, we have a value of R\$ 44.66 (US\$ 24.01) per robbery. Table 7 presents the values of estimated mean and median WTP, as defined by Eqs. (11) and (12).

¹⁷ We run an OLS regression of WTP on all variables in Table (1), and these variables are not significant.

¹⁸ To estimate this model, we use the R statistical software (R Core Team, 2014), more specifically packages “sampleSelection” (Toomet and Henningsen, 2008).

Table 6

“Global model” estimates – sample selection model with interval data.

	Selection		Outcome	
	Estimate	Stand. dev.	Estimate	Stand. dev.
(Intercept)	−0.0080	(0.1859)	2.2613	(0.1805)***
Expected loss	–	–	0.0003	(0.0000)***
Gender	−0.3432	(0.0497)***	0.1574	(0.0849)–
Age	−0.0123	(0.0016)***	−0.0070	(0.0027)**
Marital status	0.0911	(0.0501)–	–	–
Education	0.0018	(0.0156)	0.0572	(0.0184)**
Perception of patrolling	−0.0246	(0.0205)	0.0610	(0.0223)**
Victim of robbery	−0.0419	(0.0585)	0.0368	(0.0619)
Categorical subj. prob.2	0.4747	(0.1720)**	–	–
Categorical subj. prob.3	0.5036	(0.1680)**	–	–
Categorical subj. prob.4	0.6015	(0.1653)***	–	–
Categorical subj. prob.5	0.4778	(0.1570)**	–	–
Categorical subj. prob.6	0.5442	(0.1641)***	–	–
Categorical subj. prob.7	0.0756	(0.1866)	–	–
logSigma	−0.1472	(0.0225)***		
atanhRho	0.0099	(0.3181)		
sigma	0.8631	(0.0194)***		
sigmaSq	0.7449	(0.0336)***		
rho	0.0099	(0.3181)		
AIC	8068.0526			
BIC	8198.5092			
Log likelihood	−4012.026			
Num. obs.	2779			
Censored	1583			
Observed	1196			

BHHH maximization, 9 iterations.

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, – $p < 0.1$.

Source: Elaborated by the authors.

Table 7

Results of WTP(R\$) from the global parametric model.

Variable	Estimate	Stand. dev.	Inter. conf.
Mean	19.23	6.67	18.85–19.61
Median	13.25	4.59	12.99–13.51

Source: Elaborated by the authors.

The average WTP estimated from the global model is equal to R\$ 19.23 (US\$ 10.33) per month/household, which is R\$ 3.98 (US\$ 2.13) greater than the estimated value of the nonparametric form, which was R\$ 15.25 (US\$ 8.20). Thus, if the government decides to implement a monthly tax around this value, it would be possible to raise, per year, R\$ 230.76 (US\$ 124.06) per household, which would generate average tax revenue of approximately R\$ 163.9 (US\$ 88.08) million per year, which is equivalent to almost 17% of the amount spent on public security in the state of Ceará in 2011.¹⁹

Assuming a worst-case scenario, using the median WTP value of R\$ 13.25 (US\$ 7.12) per month/household as a benchmark, we have a value of R\$ 159 (US\$ 85.48) per year/household. In this case, the annual tax revenue in Fortaleza would be approximately R\$ 112.88 (US\$ 60.68) million, equivalent to 11.7% of spending on public security in 2011.

¹⁹ According to FBSP (2012), the amount spent on public security in the state of Ceará in the year of 2011 was R\$ 964,095,556.61 (US\$ 518,330,936).

Table 8

Estimates for the local model – GWR – adaptive bandwidth

	1st Qu.	Median	Mean	3rd Qu.
(Intercept)	2.4006	2.4148	2.4122	2.4266
Expected loss	0.0003	0.0003	0.0003	0.0003
Gender	0.1630	0.1743	0.1762	0.1878
Age	−0.0043	−0.0040	−0.0039	−0.0034
Education	0.0410	0.0466	0.0453	0.0490
Perception of patrolling	0.0475	0.0521	0.0530	0.0585
Victim of robbery	0.0767	0.0776	0.0828	0.0899
σ	0.7206	0.7298	0.7310	0.7383

Gaussian adaptive bandwidth = 0.6191334.

It means that each sub-sample has, approximately, 995 observations (62% of 1605 observations).

Source: Elaborated by the authors.

Now, considering the cost of robberies to society, in the first scenario, where we estimated the WTP equal to R\$ 19.23 (US\$ 10.33), we got an implicit value of a statistical robbery of approximately R\$ 9861.61 (US\$ 5301.94) per robbery avoided. Considering the second scenario, where we assumed the WTP median value equal to R\$ 13.25 (US\$ 7.12), we estimated the value of a statistical robbery at approximately R\$ 6791.81 (US\$ 3651.51) per crime avoided. Next section presents results from the local model.

6.2. Results from the local model

We estimated²⁰ the local model specified by Eq. (16). First, we present the estimated model with an adaptive bandwidth. The cross-validation technique pointed us a bandwidth (b) of 0.6191334 with a CV score of 576.9192, indicating that each sub-sample has approximately 62% of the sample. Table 8 shows the estimates under this value of b .

Now, in contrast to the global model, we have a parameter distribution for each variable. In this type of model, a tabular representation is not a good device. For pragmatic reasons we present estimates for six variables only, say, *expected loss*, *gender*, *age*, *education*, *perception of patrolling* and *victim of robbery*. So we present this result in Figs. 4–9.

For example, in the southern regions of the city of Fortaleza, the impact of variable *expected loss* is slightly greater than in others regions (the difference is in the 5th decimal place). Regarding variables *age*, *perception of patrolling*, and *victim of robbery*, the impact is greater in eastern regions. For variables *gender* and *education*, the reverse pattern occurs. The impact is greater in western regions.

Note that with this parameter distribution, it is possible to create a willingness to pay's distribution. We plug in the parameter vector into each individual's vector of observations and calculate the expected willingness to pay and sort them into five classes. Fig. 10 shows us the spatial distribution of willingness to pay.

To facilitate analysis, we constructed an interpolated surface to predict the willingness to pay for the entire city of Fortaleza by the ordinary Kriging techniques.²¹ Fig. 11 shows the estimated surface.

The highest values of estimated willingness to pay are concentrated in three big clusters (the upper-left “Horseshoe” area, orange colored): (i) the central region of the city. This is the area where the greatest amount of robberies in the city is concentrated (downtown Fortaleza); (ii) the southwest region of Fortaleza, an economically deprived area and historically a violent place; and (iii) the north side, especially around the shabby seaside areas of “Pirambu”, “Barra do Ceará”, and “Praia de Iracema”.

A possible mechanism to explain Fig. 11 goes like that: it is costly to invest in precautions, so not everyone will invest, but people care about the amount that potentially he/she can lose in a robbery, as well. This implies that the probability of buying precaution is increasing in the subjective probability of being robbed times income. This means

²⁰ To estimate this model, we use the R statistical software (R Core Team, 2014), more specifically packages “maxLik” (Henningsen and Toomet, 2011) and “spgwr” (Bivand and Yu, 2013).

²¹ For more details of this method, see, among others Druck et al. (2004) and Bivand et al. (2008).

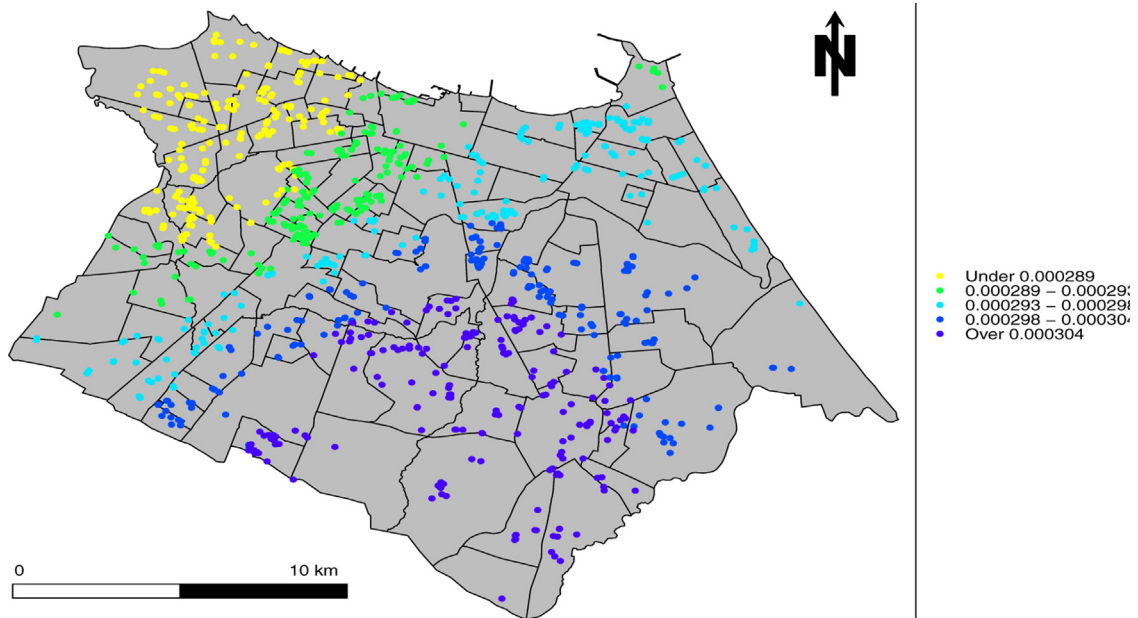


Fig. 4. Estimated parameters of spatial distribution – expected loss.

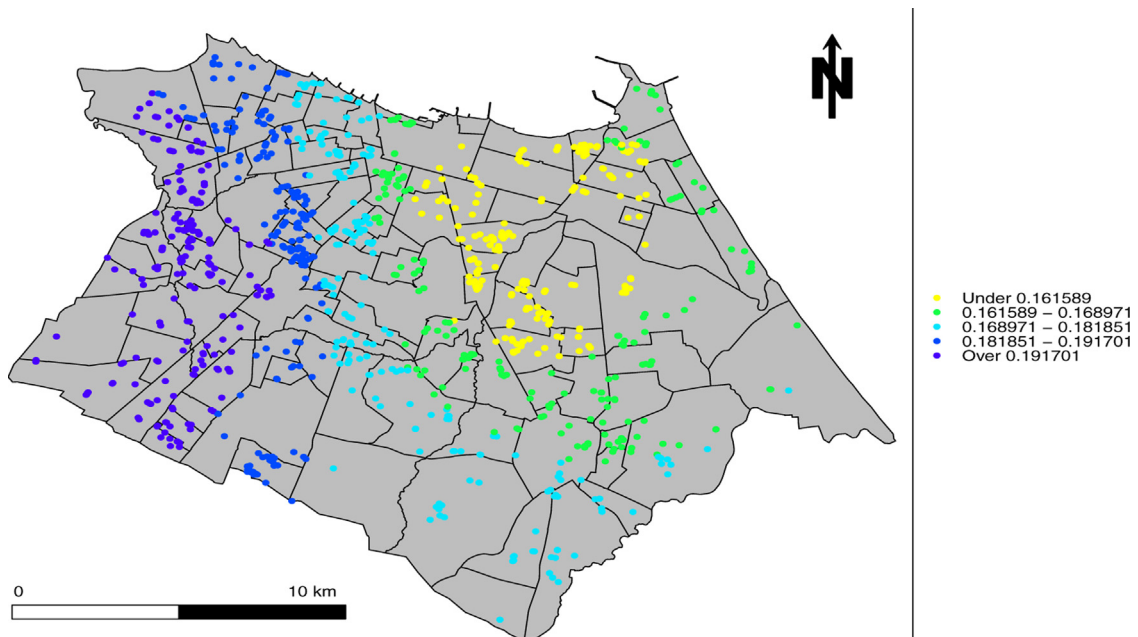


Fig. 5. Estimated parameters of spatial distribution – gender.

that low-income areas could have high WTP, by the same token, we could have high-income areas with higher WTP, as those very individuals might have more valuable items to get robbed even though they can invest in protection. What our empirical exercise delivered seems to be an interesting evidence: in Fortaleza (Brazil), poor people have surprisingly higher willingness to pay for robbery than rich individuals, although the very spatial distribution of WTP is heterogeneous.

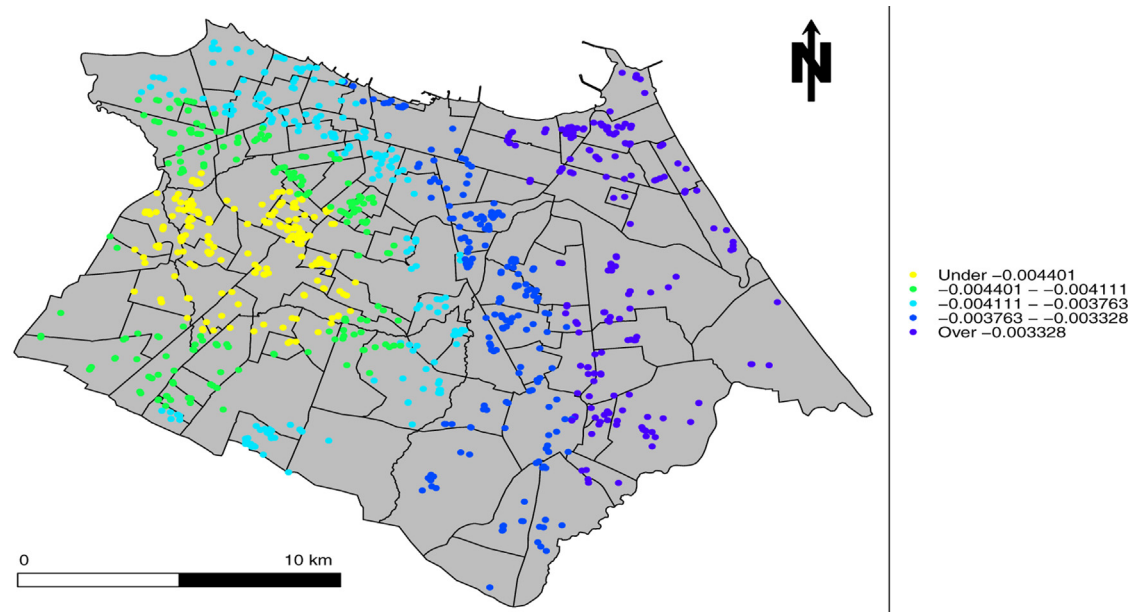


Fig. 6. Estimated parameters of spatial distribution – age.

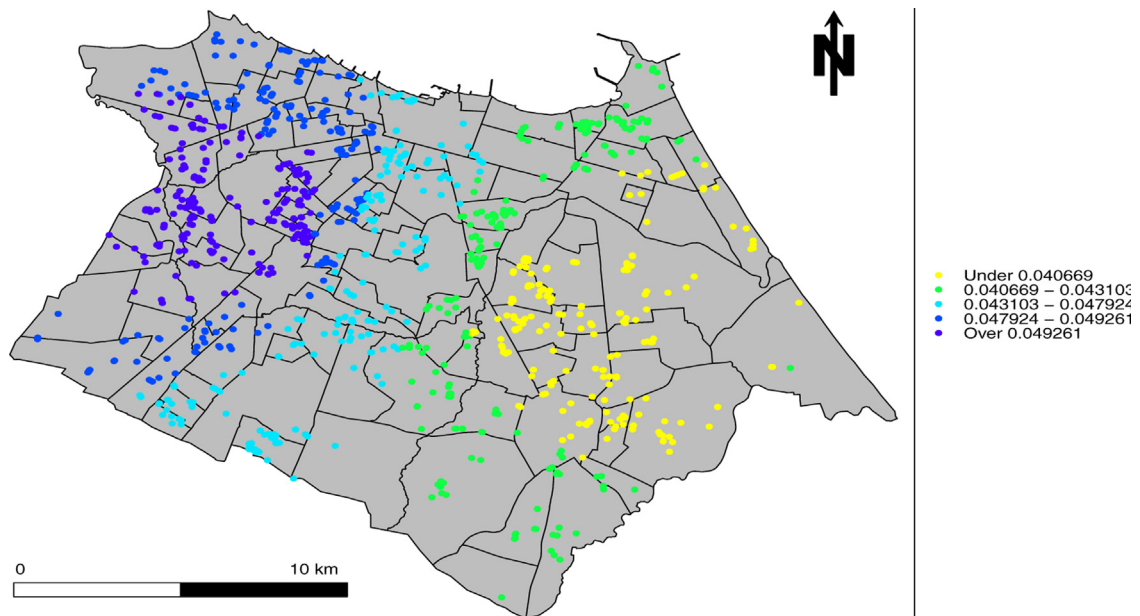


Fig. 7. Estimated parameters of spatial distribution – education.

The heterogeneity in the spatial distribution of crime²² may add another layer of complexity and is an additional explanation for the spatial heterogeneity in WTP. Interesting, when we compare the estimates' values from the local model to those from the global model, we can see that the willingness to pay in much of the city is higher than the average global willingness to pay of R\$ 19.23. This difference is likely due to the fact that we did not manage to control for selection on the global model.

²² Figs. 16 and 17 presented in Appendix 3 shows the spatial distributions of homicides and robberies in Fortaleza.

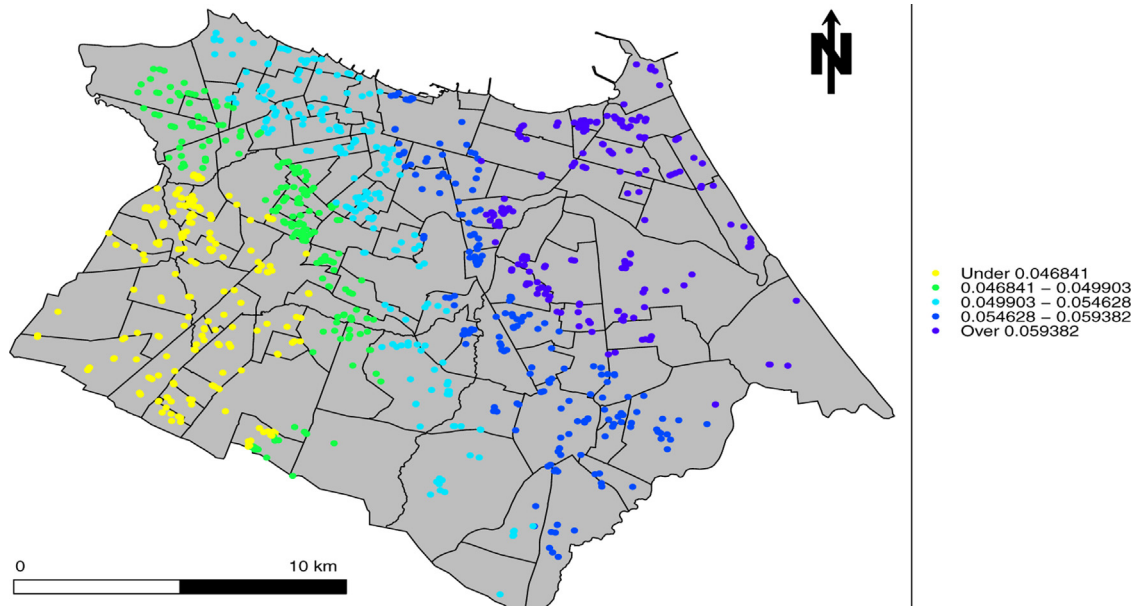


Fig. 8. Estimated parameters of spatial distribution – perception of patrolling.

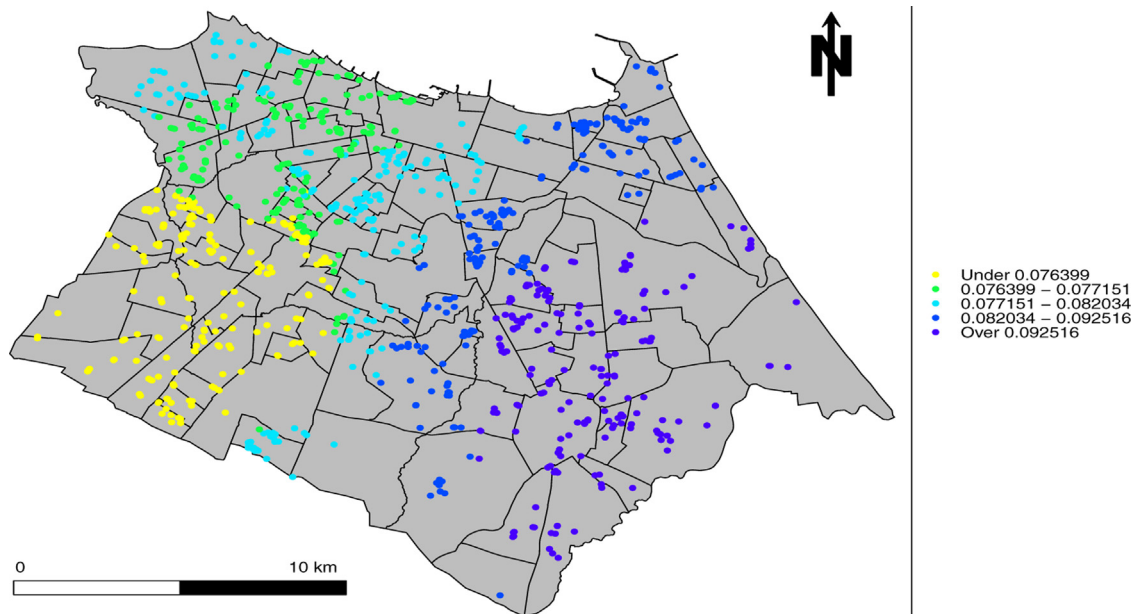


Fig. 9. Estimated parameters of spatial distribution – victim of robbery.

7. Final considerations

We sought to apply a new methodological approach to estimate willingness to pay for crime reductions in a large urban center in Brazil. We built a theoretical model that explains the determinants of willingness to pay for a first-order stochastic improvement on the odds of being robbed in the city of Fortaleza (Brazil) when subjective expectations are available.

We showed that the most important factors explaining the decision between to pay or not any positive value in the city of Fortaleza (Brazil) are *gender*, *age*, *marital status*, and *categorical subjective probability*, while the determinants

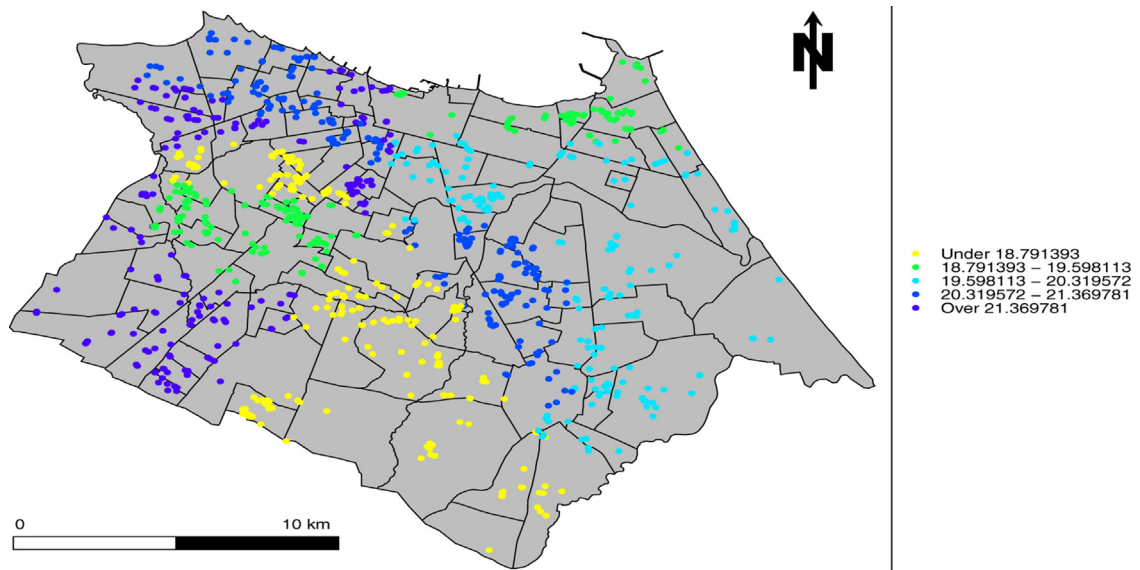


Fig. 10. Willingness to pay – spatial distribution.

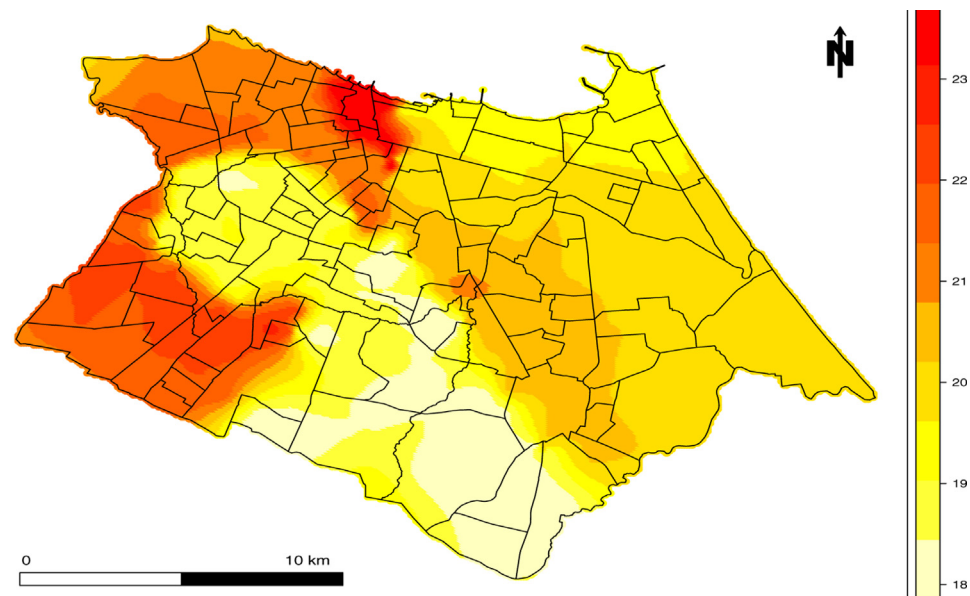


Fig. 11. Willingness to pay – kriging surface.

of the value paid are represented by variables such as *expected loss*, *gender*, *age*, *education*, *perception of patrolling*, and *victim of robbery*.

From the global model, we estimated a mean WTP of R\$ 19.23 (US\$ 10.33) per month as the value that a representative citizen of Fortaleza would be willing to pay to reduce the probability of robbery in the city by 50%. From this value, we calculated in almost R\$ 163.9 (US\$ 88.08) million the total cost to society, equivalent to approximately 17% of the total amount spent on public security in the state of Ceara in 2011. We also estimated the WTP per robbery avoided equal to R\$ 9861.61 (US\$ 5301.94).

Our local model, utilizing an adaptive Gaussian kernel function with a bandwidth equal to approximately 0.62, estimated a geographically weighted regression with an interval regression that, to the best of our knowledge, it is the

first study to do so. We showed that in much of the city, the willingness to pay estimated in the local model is higher than one estimated in the global model.

As suggestions for future studies, we believe that the construction of a new model relaxing the hypothesis of risk neutrality is a fine way to go. Finally, replicating our empirical exercise on different datasets coming from different institutional backgrounds might be something worth pursuing in order to validate our approach.

Appendix 1 Model

Our objective is to build a contingent valuation model to assess willingness to pay for a stochastic improvement on the odds of being robbed in the city of Fortaleza, Brazil when individual subjective expectations about the risk are available. Before we provide more context about what we mean by a “stochastic improvement”, we start our analysis by defining the following objects:

- 1 A binary random variable $R \in \{0, 1\}$ as an indicator that “a shock (robbery) did not happen” ($R=0$) or “a shock (robbery) happened” ($R=1$)
- 2 A continuous random variable $M \in \mathbb{R}_+$ measuring shock’s monetary cost (tangible and intangible costs)
- 3 A binary random variable $\theta \in \{0, 1\}$ as an indicator of *status-quo* situation ($\theta=0$) or alternative status to be achieved with transfers ($\theta=1$)
- 4 A mixed (continuous and/or discrete) random variable $X \in \mathbb{R}^K$ representing a vector of individual and/or state-specific characteristics
- 5 A variable $s_i \in [0, s^{max})$ representing (irreversible) monetary transfers from each individual $i = 1, 2, \dots, N$ to finance the change between *status-quo* and alternative situations

In addition, we assume the following three hypotheses, say, for each individual $i = 1, 2, \dots, N$ at each $\theta \in \{0, 1\}$:

Hypothesis 1. Each individual is risk neutral and has preferences over a compound lottery equivalent to preferences over the corresponding reduced lottery.

Hypothesis 2. Each individual is endowed with an(conditional on X) indirect utility function given by $V_{i,\theta} = V(y_i, \theta|X)$, where y_i is a sure amount of money.

Hypothesis 3. Each individual is endowed with a well-defined (conditional on X) probability of shock (robbery) occurrence $P_{R|X}^{i,\theta}(r|X = x)$ and a well-defined (conditional on R, X) density function for M , say, $P_{M|R,X}^{i,\theta}(m|R = 1, X = x)$.

Finally, we assume the following about the expected value of M :

Hypothesis 4. The expected value of M is finite, i.e., $E(M|X) = \int_M m P_{M|R,X}(m|R = 1, X) dm < \infty$.

Now we can be more specific about our concept of “stochastic improvement”. Remember that the counterfactual proposed by question 105 in [Carvalho \(2012\)](#) was phrased like that:

“...to cut in half the occurrence of personal robbery in Fortaleza...”.

So, it is important to note that the proposed change in *status-quo* is a change only on $P_{R|X}^{i,\theta}(r|X = x)$, and not in $P_{M|R,X}^{i,\theta}(m|R = 1, X = x)$. Using the nomenclature in [Seog \(2010\)](#), the proposed change acts only on the probability of “loss occurrence” $P_{R|X}^{i,\theta}(r|X = x)$ and not on the probability of “loss size” given “loss occurrence” $P_{M|R,X}^{i,\theta}(m|R = 1, X = x)$.

For $\theta \in \{0, 1\}$, the payoffs associated with $P_{R|X}^{i,\theta}(r|X = x)$ are $\{-E(M|X), 0\}$, and $P_{M|R,X}^{i,\theta}(m|R = r, X = x)$ will not change. The “stochastic improvement” stems from the fact that the proposed change in *status-quo* is equivalent to $Pr_{R|X}^{1,i} = \frac{1}{2} \times Pr_{R|X}^{0,i}$. It is easy to see that equivalence means $P_{R|X}^{i,1}(r|X = x) \geq_{FSD} P_{R|X}^{i,0}(r|X = x)$, where \geq_{FSD} means first-order stochastic dominance, see, [Fig. 12](#):

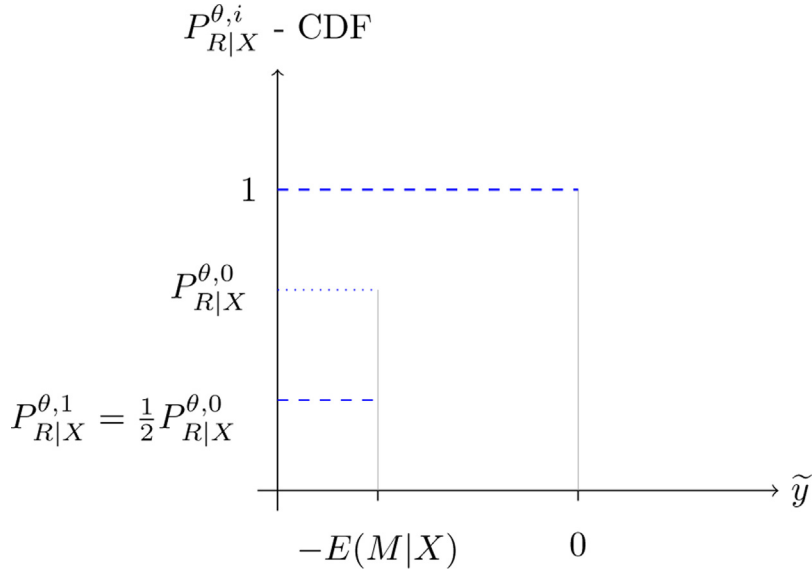


Fig. 12. First order stochastic dominance.

Given that, our (willingness to pay) problem is to find a s_i which makes $E(V_{i,0}|X) = E(V_{i,1}|X)$:

$$E(V_{i,0}|X) = \left[\int_M V(y_i - m, 0|X) P_{M|R,X}^{i,0}(m|R=1, X) dm \right] P_{R|X}^{i,0}(r=1|X) + V(y_i, 0|X) (1 - P_{R|X}^{i,0}(r=1|X)) \quad (17)$$

$$E(V_{i,1}|X) = \left[\int_M V(y_i - s_i - m, 1|X) P_{M|R,X}^{i,1}(m|R=1, X) dm \right] \times P_{R|X}^{i,1}(r=1|X) + V(y_i - s_i, 1|X) (1 - P_{R|X}^{i,1}(r=1|X)) \quad (18)$$

Eqs. (17) and (18) depend on many subjective “counter-factual” objects like $P_{M|R,X}^{i,1}(m|R=1, X)$, and the likely functional form for the indirect utility function. In order to focus on the essential, we make some simplifying assumptions:

Hypothesis 5. $\forall i, i' \in \{1, 2, \dots, N\}$ and $\theta, \theta' \in \{0, 1\}$, $P_{M|R,X}^{i,\theta}(m|R=1, X=x) = P_{M|R,X}^{i',\theta'}(m|R=1, X=x) = P_{M|R,X}(m|R=1, X)$.

Hypothesis 6. Except for $P_{R|X}^{i,\theta}(r|X=x)$, the distribution functions are equal to its respective objective distribution.

Hypothesis 7. The indirect utility function for each $\theta \in \{0, 1\}$, and any individual $i \in \{1, 2, \dots, n\}$ is parameterized as $V(\tilde{y}_i, \theta|X) = \beta \tilde{y}_i + \alpha_\theta X_i$

Now, our two quantities of interests assume the following expressions:

$$E(V_{i,0}|X) = \left[\int_M (\beta(y_i - m) + \alpha_0 X_i) P_{M|R,X}(m|R=1, X) dm \right] \times P_{R|X}^{i,0}(r=1|X) + (\beta y_i + \alpha_0 X_i) (1 - P_{R|X}^{i,0}(r=1|X)) \quad (19)$$

$$E(V_{i,1}|X) = \left[\int_M (\beta(y_i - s_i - m) + \alpha_1 X_i) P_{M|R,X}(m|R=1, X) dm \right] \\ \times P_{R|X}^{i,1}(r=1|X) + (\beta(y_i - s_i) + \alpha_1 X_i) \left(1 - P_{R|X}^{i,1}(r=1|X) \right) \quad (20)$$

From Eqs. (19) and (20), we have:

$$\beta \left(y_i - E(M|X) Pr_{R|X}^{i,0}(r=1|X) \right) + \alpha_0 X_i \quad (21)$$

$$\beta \left(y_i - s_i - E(M|X) Pr_{R|X}^{i,1}(r=1|X) \right) + \alpha_1 X_i \quad (22)$$

Now we are able to develop the expression for the willingness to pay by equating Eqs. (21) and (22), and solving for s_i .

$$s_i = E(M|X) \left(Pr_{R|X}^{i,0}(r=1|X) - Pr_{R|X}^{i,1}(r=1|X) \right) + \frac{(\alpha_1 - \alpha_0)}{\beta} X_i \quad (23)$$

First note that the expression for the willingness to pay s_i depends on a vector of independent variables, X_i , as well on an additional variable: the difference on the expected value of the shock between the *status quo* and the new situation, say, $E(M|X)Z_i$, where $Z_i = Pr_{R|X}^{i,0}(r=1|X) - Pr_{R|X}^{i,1}(r=1|X)$. Now, we have to make an assumption about $E(M|X)$. We can assume either one of the following:

Hypothesis 8. $E(M|X) = \tau$, a constant. A sufficient condition for that is to assume the distribution of shock's size to be independent from the observed heterogeneity, X , i.e., $P_{M|R,X}(m|R=1, X) = P_M(m)$.

Hypothesis 9. $E(M|X) = \tau Y$, i.e., the expected value of the robbery is proportional to the individual household's *per capita* income.

Hypothesis 10. $E(M|X) = \sum_k \exp(\lambda_k X_{ik})$.

Hypothesis 11. $E(M|X) = \exp(\sum_k \lambda_k X_{ik})$.

Since the individual is risk neutral, it seems “natural” that income does not have a bite on the willingness to pay. However, this is so as long as the expected value of the shock does not depend on Y (All above, except Hypothesis 9). Indeed, assuming $E(M|X) = \tau Y$ is backed by well-established anecdotal (rich people buy and exhibit (many times show off) more valuable goods) and some scientific literature (see [Dominguez-Rivera and Steven \(2015\)](#)). Note that τ does not necessary belongs to $(0, 1)$ as Y is household *per capita* income, though.

However the appeal of $E(M|X) = \sum_k \exp(\lambda_k X_{ik})$ or $E(M|X) = \exp(\lambda X_i)$ and the fact that the vector of parameters λ would be identified,²³ we stick to more pragmatic assumptions such as $E(M|X) = \tau$ and $E(M|X) = \tau Y$. Defining the vector $\varphi \equiv \frac{(\alpha_1 - \alpha_0)}{\beta}$ and plugging in an error term, we get the following estimable equation if we assume $E(M|X) = \tau$:

$$s_i = \varphi_0 + \varphi_1 X_{i1} + \varphi_2 X_{i2} + \dots + \varphi_k X_{ik} + \tau Z_i + \epsilon_i \quad (24)$$

We have estimated several variants of Eq. (24), both at levels or logs, and found results unrealistic. We then stick to hypothesis $E(M|X) = \tau Y$, and get the following estimable equation:

$$s_i = \varphi_0 + \varphi_1 X_{i1} + \varphi_2 X_{i2} + \dots + \varphi_k X_{ik} + \tau Y_i Z_i + \epsilon_i \quad (25)$$

We can get a logarithmic version of Eq. (25) by a first order Taylor's expansion, as long as we re-scale monetary values s_i to belong to the interval $(0, 1]$. We can achieve that by dividing both sides by s^{max} , the upper bound on willingness to pay. Although we do not see s^{max} , we can consistently estimate s^{max} , by $\max(s_1, s_2, \dots, s_N)$. We side

²³ We left this assumption for a future empirical exercise.

Table 9
Kolmogorov–Smirnov test.

Variables	Statistic	<i>p</i> value
Subject prob.	0.0481	0.0685
Income	0.0199	0.9431
Gender	0.1396	0.0000
Age	0.1086	0.0000
Education	0.0394	0.2070
Perception of patrolling	0.0132	0.9996
Victim of robbery	0.0074	1.0000
Marital status	0.0028	1.0000
Categorical subj. prob.	0.0370	0.2693
Expected loss	0.0407	0.1913

H_0 : Distributions are equal.

Source: Elaborated by the authors.

step any unnecessary complication and assume that $\max(s_1, s_2, \dots, s_N) = s^{\max}$, and use $s^{\max} = R \$ 100.00$ to represent both the estimation and the parameter. Here it is the new functional form:

$$\ln(s_i) = \left(\frac{\alpha_0}{s^{\max}} - 1 + \ln(s^{\max}) \right) + \frac{\alpha_1}{s^{\max}} X_{i1} + \frac{\alpha_2}{s^{\max}} X_{i2} + \dots + \frac{\alpha_k}{s^{\max}} X_{ik} + \frac{\tau}{s^{\max}} Y_i Z_i + \epsilon_i \quad (26)$$

Let $\varphi_0 \equiv \left(\frac{\alpha_0}{s^{\max}} - 1 + \ln(s^{\max}) \right)$, $\varphi_j \equiv \frac{\alpha_j}{s^{\max}}$, $j = 1, \dots, k$ and $\varrho \equiv \frac{\tau}{s^{\max}}$. In that case, our estimable equation takes the following form:

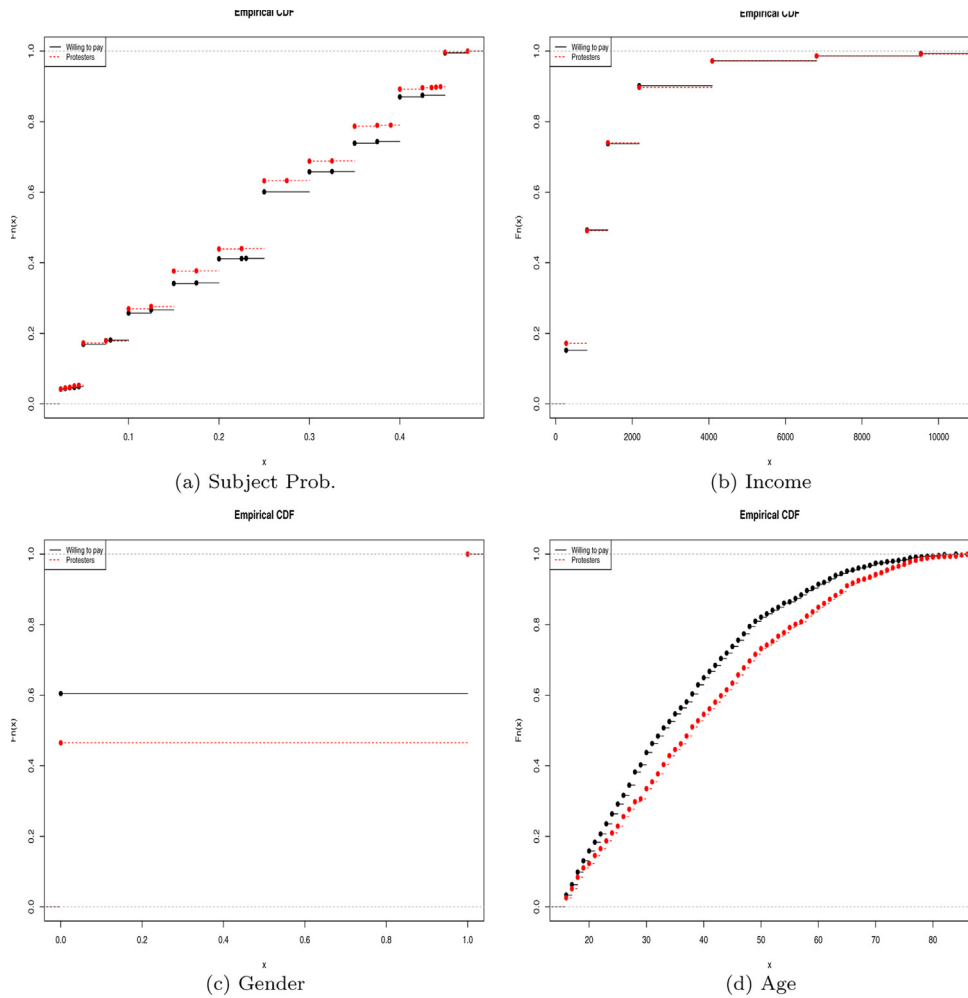
$$\ln(s_i) = \varphi_0 + \varphi_1 X_{i1} + \varphi_2 X_{i2} + \dots + \varphi_k X_{ik} + \varrho EL_i + \epsilon_i \quad (27)$$

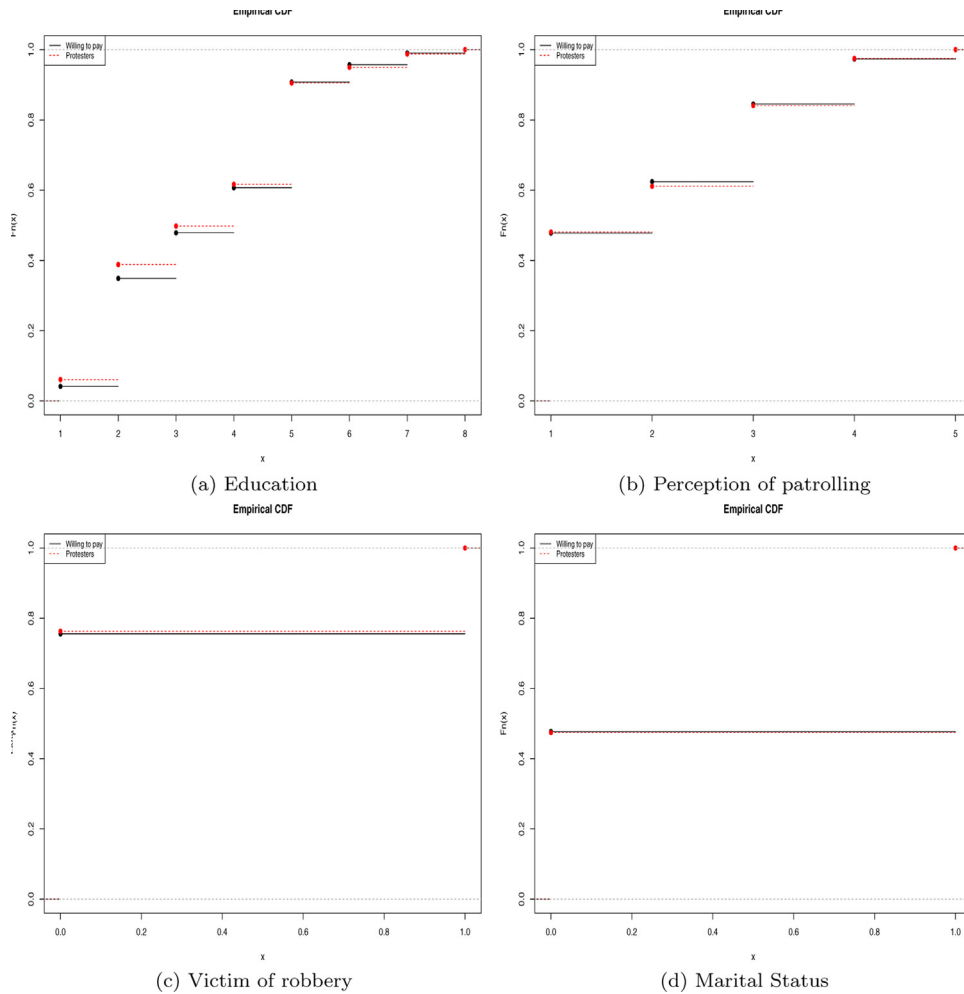
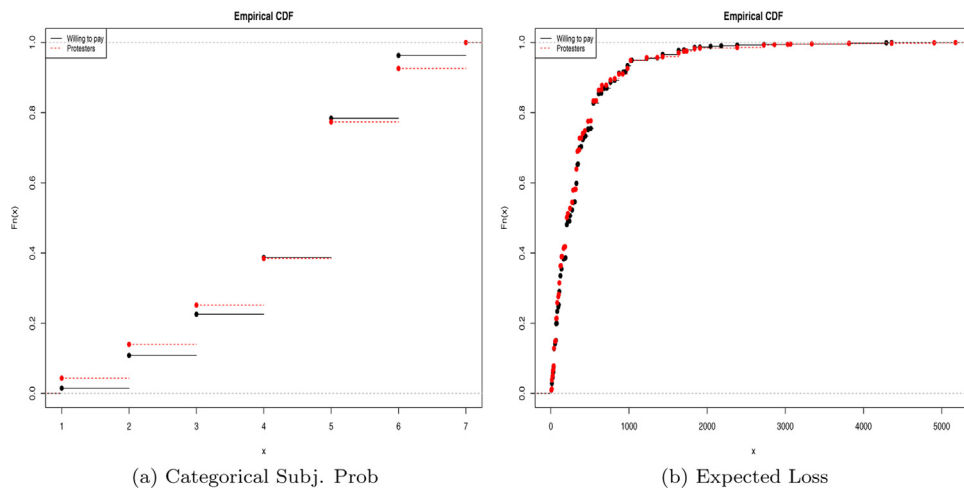
where $EL_i = Y_i Z_i$ is the expected loss.

Appendix 2 Supplements

See [Table 9](#) and [Figs. 13–15](#).

Appendix 3 Spatial distributions of crimes in Fortaleza

Fig. 13. Empirical CDF protesters *versus* willing to pay.

Fig. 14. Empirical CDF protesters *versus* willing to pay (Cont.).Fig. 15. Empirical CDF protesters *versus* willing to pay (Cont.).

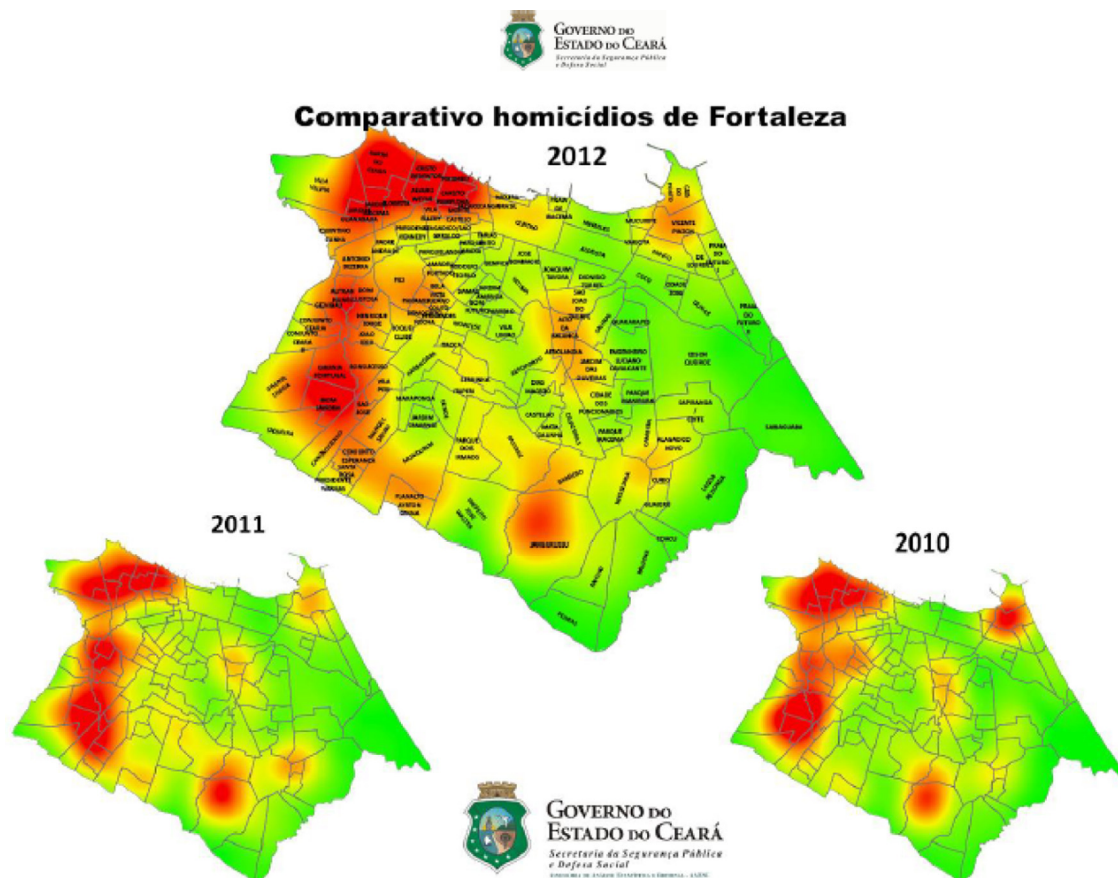


Fig. 16. Spatial distributions of homicides in Fortaleza between 2010 and 2012.

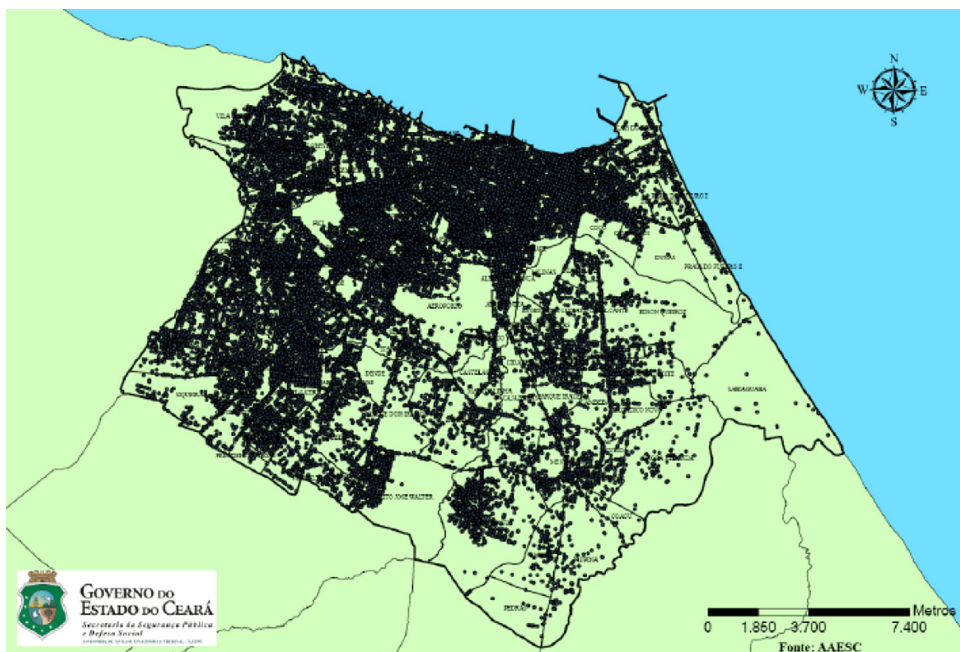


Fig. 17. Spatial distributions of robberies in Fortaleza between 2012 and 2013.

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