Spatial Willingness to Pay for a First Order Stochastic Reduction on the Risk of Robbery

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Abstract

The aim of this paper is to estimate willingness to pay (WTP) for a first order stochastic reduction on the risk of crimes for residents of a large and dense urban center. Inspired by Cameron and DeShazo (2013), we develop a simple structural choice model that nests a process of contingent valuation (CV) among lotteries and estimate it by both parametric maximum likelihood and geographically weighted regression (GWR). Our empirical support is a unique and rich micro data set about victimizaton in Fortaleza, CE (Brazil). For the global model (i.e., without spatial effects), we estimated an average WTP of R$ 23.35 per month/household, and an implicit value of a statistical robbery approximately equal to R$ 11,969 per crime avoided. By means of geographically weighted regression (GWR), we find that variables *Sex*, *Age* and *Education* present a reasonable amount of spatial heterogeneity and, as expected, follow the very inertial city's socioeconomic spatial distribution profile. We implement as well a protocol to calculate a surface of WTP using Kriging techniques. Income, age, and crime spatial distributions have important effects on the surface of WTP. Although peripheries present lower willingness to pay, as long as we go inwards there is plenty of heterogeneity on its spatial distribution for risk reductions. Our results supports a theory of crime with an active role for victim (costly) precautions.

Keywords: Urban Crime, Contingent Valuation, Spatial Effects - **JEL Codes**: O18, Q51, C31.

Resumo

O objetivo deste trabalho é estimar a disposição a pagar (DAP) para uma redução estocástica de primeira ordem sobre o risco de crimes para residentes de um grande e denso centro urbano. Inspirado por Cameron and DeShazo (2013), desenvolvemos um modelo estrutural de escolha simples que aninha um processo de avaliação contingente (AC) entre loterias e o estimamos tanto por máxima verossimilhança paramétrica quanto por regressão geograficamente ponderada (RGP). Nosso suporte empírico é uma rica base de microdados sobre victimização única para Fortaleza, CE (Brasil). Para o modelo global (ou seja, sem efeitos espaciais), estimamos uma DAP média de R$ 23,35 por mês/família, e um valor estatístico implícito de um assalto aproximadamente igual a R$ 11,969 por crime evitado. Por meio de regressão geograficamente ponderada (RGP) constatamos que as variáveis *Sex*, *Idade* e *Educação* apresentaram valores razoáveis de heterogeneidade espacial e, como esperado, segue o perfil bastante inercial da distribuição espacial socioeconômica da cidade. Implementamos também um protocolo para calcular uma superfície de DAP usando técnicas de krigagem. As distribuições espaciais de renda, idade e crime possuem efeitos importantes sobre a superfície de DAP. Embora periferias apresentem menor DAP, á medida que nos dirigimos para o centro da cidade, há muita heterogeneidade na distribuição espacial para a redução de riscos. Nossos resultados suportam uma teoria do crime com um papel ativo para precauções (financeiramente relevantes) por parte da vítima.

Palavras-Chave: Crime Urbano, Avaliação Contingente, Efeitos Espaciais - **Código JEL**: O18, Q51, C31.

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1 Introduction

Contingent Valuation (CV) is a method that has been widely used in recent decades. Its foremost objective is to infer, through public opinion's surveys, the value of certain goods that are not readily tradable on traditional markets, such as public goods and natural resources. This method consists in constructing a hypothetical market for a certain good, as realistic and structured as possible, such that, by performing a survey, researchers can extract the maximum willingness to pay of individuals for that good[1]. Bowen (1943) and Ciriacy-Wantrup (1947) were the pioneers to propose the use of public opinion's 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 the public opinion's surveys would be a valid instrument for valuation of these goods (Hoyos and Mariel 2010, Carson and Hanemann 2005).

Although the main goal of contingent valuation method has been measuring the monetary value of a certain good for a individual (Carson and Hanemann 2005), there is a much more powerful insight on top of it: welfare analysis. According to Hoyos and Mariel (2010), through contingent valuation surveys is possible to obtain directly a monetary measure (Hicksian) of welfare associated with a discrete change in the provision of an environmental good, either by 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 for the agent, we following Whitehead and Blomquist (2006) and Carson and Hanemann (2005). Define a utility function that, for simplicity, only depends on a good x and contingent good q, given by $u(x, q)$. Thus, assuming that the good q is desirable, and that q^0 is the state in which the consumer has not the good and q^1 is the state that the consumer has access to the good, the consumer will pay to consume the good if, and only if, the utility obtained with the consumption of the good is greater than the utility obtained without the consumption of good, i.e., $u^1(x, q^1) > u^0(x, q^0)$.

So, the consumer will maximize his utility function $u(x, q)$, subject to his 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 $v(p, q, y)$, whose usual properties with respect to 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 a expenditure function given by $e(p, q, u)$, see (Mas-Colell, Whinston, and Green 1995). According to Carson and Hanemann (2005), the value for the individual, in monetary terms, of 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. As shown by (Mas-Colell, Whinston, and Green 1995). Formally, those measures are solutions to the following equations, respectively:

$$v^1(p, q^1, y - C) = v^0(p, q^0, y) \tag{1}$$

$$v^1(p, q^1, y) = v^0(p, q^0, y + E) \tag{2}$$

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

[1]There is the concept of minimum willingness to accept, where the individual reporting the minimum amount for which he would be willing to accept to give up consuming a good that he would have been entitled. However we will not cover this side.

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, DeShazo, and Stiffler (2010) and Cameron and DeShazo (2013) are notably exceptions.

Although the scope of applicability of the method has grown considerably, many key areas traditionally approached by economists has not been thoroughly touched upon by contingent valuation. A notable example is crime. Since problems of measurement, externalities, and difficulties in assessing costs plague the area of crime and economics, it appears to us that such state of affairs can not be understood. In fact, very few papers so far has applied the contingent method internationally and, at a national level, we are aware of only one.

Ludwig and Cook (2001) estimates the benefits of reducing crime using this method. In their paper, Ludwig and Cook (2001) focus on gun violence, in a national survey in U.S. Using a parametric form, they found a value of US$ 24.5 billion as the worth for American society for a 30% reduction in gun violence or US$1.2 million per injury avoided. Still in the U.S., Cohen, Rust, Steen, and Tidd (2004) using a nationally representative sample of 1,300 U.S. residents, found that the representative American household would be willingness to pay between US$ 100 and US$ 150 per year for programs that reduced specific crimes by 10% in their communities. Cohen, Rust, Steen, and Tidd (2004) analyzed five types of crimes: burglary, serious assault, armed robbery, rape or sexual assault and murder.

In the U.K., Atkinson, Healey, and Mourato (2005) valuated the cost of three violente crimes: common assault (no injury), other wounding (moderate injury) and serious wounding (serious injury). Theirs data set contained 807 observations in Wales and England. In the interview, respondents were told that the probability of being victim of the select crime, 4% for common assault and 1% for both other wounding and serious wounding, then each respondent was asked to express his WTP to reduce his chance of being victim of this offense by 50% over the next 12 months. The estimated values for WPT encountered by them was £ 105.63, £ 154.54 and £ 178.33 for common assault, other wounding and serious wounding, respectively.

Finally, in Portugal, Soeiro and Teixeira (2010) studied the determinants of higher education students' willingness to pay for reducing the risk of being victim of violent crimes. They conducted a online survey with students of university of Porto, which had 1122 respondents. By means of a parametric approach, they modeled WTP as a function of demographic factors (age and gender), family related factors (income, dimension, dependents), degree (undergraduate, master, PhD) and field of study (economics, arts, ...), crime related factors (crime victim, crime time, physical injuries, psychological damages, fear of crime), averting behaviour (lock the door), payment vehicle and policy. They found that variables such as age and family members had a negative impact in WTP whereas variables such as gender, fear of crime lock door and payment vehicle had a positive impact on willingness to pay.

In Brazil, Araújo and Ramos (2009) used contingent valuation to estimate the loss of welfare associated to insecurity, utilizing the willingness to pay as a proxy. The survey was conducted in the city of ***João Pessoa*** and had 400 observations. Respondents were asked how much they would be willing to pay by a bundle of public security services, that contain: fixed police posts equipped with adequate weaponry; vehicles equipped for better care and effective police action; officers trained, with greater integration with the community and greater agility (speed) in citizen service; day and night patrols and conducting educational programs to prevent violence and crime. They found that public security is a normal and common good as well as that the estimated cost of insecurity in ***João Pessoa*** varies between R$ 6.524.727,01, considering the most conservative estimative, and R$ 104.864.863,52 for the highest value.

Although Ludwig and Cook (2001), Cohen, Rust, Steen, and Tidd (2004), Atkinson, Healey, and Mourato (2005), and Soeiro and Teixeira (2010) propose valuations between non-degenerate lotteries, they stopped very far from building a econometric model that incorporates the basic tenets of choice under risk. Given that state of affairs (lack of a conceptual empirical strategy for CV among "lotteries", and, incipient literature on willingness to pay for crime reduction policies), our main contributions are: i) to build (and estimate) a econometric model capable of assessing the willingness to pay for first order stochastic reduction in the risk of robbery, ii) to incorporate, in a sensible and manageable way, spatial effects to realistically mimics interactions present in a large and densely populated urban center in Brazil, and, iii) to apply our empirical strategy to real data, more specifically, to Brazilian data.

We believe to have succeeded in a satisfactorily way. We make use of a unique geo-referenced sample of 4,030 households from the city of Fortaleza, CE (Brazil), containing information on socioeconomic background, experience, expectation of victimization, and willingness to pay to reduce some type of crimes (see, Carvalho (2012)). For the global model (i.e., without spatial effects), the parameters for all independent variables, except ***Age***, show positive sign. Older people tends to pay less to reduce crime than young people do, men and more educated people tends to pay more risk reductions. Finally, as to variables of perception and experience of victimization (variable ***Perception patrol*** is measured in decreasing order), the lower the perception of patrolling the greater the willingness to pay to reduce the number of robberies, and people who was ***Victim of robbery*** tends to pay more to prevent such experience again. We estimated as well an average willingness to pay of R$ 23.35 per month/household, a higher value of R$ 5.91 than the estimated value of non parametric form. Also, we estimated the implicit value of a statistical robbery approximately equal to R$ 11,969 per crime avoided. Both values are quite reasonable. As a matter of fact, our proposed specification made possible to estimate implicitly the average cost of each robbery in the city of Fortaleza. This amounts to approximately 4,15% of the income. Multiplying this value by average income we have a value of R$ 61,38 per robbery.

The full spatial heterogeneity reveals with our "local model". By means of a geographically weighted regression (GWR) it is possible to allow for the estimation of local parameters rather than global parameters (Fotheringham, Brunsdon, and Charlton 2003). Now, the first difference is the lack of a unique estimated parameter for each independent variable. Instead, for each independent variable, we have a possible different parameter for each sampled point. Overall, the estimated spatial heterogeneity bring us both expected results as well as surprises. The estimative mapping for variables ***Sex***, ***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 implement a protocol to calculate a surface of willingness to pay. In order to do that we apply Kriging techniques. The image that emerges from such empirical exercise is not difficulty to rationalize: the income, age, and crime spatial distribution of Fortaleza has an important effect on the surface of willigness to pay. Although 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 robbery reduction. It is worth noting that the highest willingness to pay are not necessarily the richest one, corroborating a theory of crime that posits an active role for victim (costly) precautions.

Besides this introduction, we have more 5 Sections. Section (2) introduces the data set employed in our estimatives. Section (3) develops a simple structural model of contingent choice between lotteries of risks and frame the resulting equation as a fully parametric econometric model, although, given the type of data collected we end up estimating it by fully maximum likelihood. In order to introduce our spatial effects, Section (4) deals with geographically weighted regression and how to manage that in our context. We call such model the "Local" to contrast with the previous one that neglect spatial effects. All estimatives are performed on Section (5), as well as the due interpretations from the estimation exercises. Finnaly, Section (6) elaborates more on results and proposes futures improvements.

2 Data Set

Our data set comes from a survey conducted in 2012 where a total of 4,030 households were sampled along 119 districts (*bairros*) of the city of Fortaleza (Brazil) during the months of October 2011 to January 2012, see, Carvalho (2012). Besides information about socioeconomic background, experience and expectation of victimization, Carvalho (2012) induced respondents express their willingness to pay to reduce some type of crimes. a key component from the data set collected is due to the fact that household, work and school positions were georeferenced.

The section about contingent valuation prsents respondents with a fictional scenario where there was a program to fight against criminality, more specifically the crime of robbery. The respondent was informed that the program was successful and succeeded in reducing 50% the amount of robberies. However, to maintain this program, it was necessary that the population fund it by means of fictitious future taxes. Then, respondents were asked if they were willing to pay a monthly fee to maintain that crime prevention program, and if so, by how much he would be willing to pay monthly. The exact introduction and 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.***

- 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 in half the occurrence of personal robbery in Fortaleza. Would you be willing to pay a monthly amount to keep this program of crime prevention?***

Table 1 defines the variables used in this paper. Initially, we show the socioeconomic profile, the perception of security and experience of victimization of research participants. From a total of 4,030 observations in the initial sample, 246 observations were removed due to lack of information about participation in the program and due to the difficult in georeferencing respondent's address. Table 2 shows that 44,66% of the respondents were men and 55,34% were women. Overall age of the respondents were 39,45 years old, with completed fundamental school level. About income, the average income was R$ 1,488.70 per month, but about 50% of respondents earn R$ 817.50 or less[2].

As to victimization and perception of security, 23,24% of the respondents was victim of robbery in the last five years at least once. As to perception of security, on average, respondents considered that the probability of being robbed in the next 12 months is about 49.2%, although the perception patrols is often (mean 2.05).

Out of 3,784 respondents, 1,709 (45,16%) answered that they are willing to pay a monthly fee to fund the program to combat robberies, while 2,076 (54,86%) answered they would not pay any amount. Despite the number of people who are not willing to pay to keep the programs to combat crime is fairly high, it is consistent with other studies about contingent valuation, for instances, Atkinson, Healey, and Mourato (2005), which had 34,57%, and Araújo and Ramos (2009), which had a rate of 48.5 %, the last one for the city of João Pessoa (Brazil). This second group is defined in the contingent valuation area as *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 it is responsibility of the government the provision of such goods, or simply because it is the duty of other groups pay for the provision of good[3]. However, it is possible that someone report a true zero value for the reduce of risk of being robbed or just can not afford to pay such amount.

[2]The minimum wage in Brazil at the time of the survey was equal to R$ 545,00.

[3]We also consider the fact that individuals do not reporting his willingness to pay for fear that, once answered a value, the research can be used to make them pay the reported amount.

Table 1: Variables

Variable	Description
Sex	1 if male; 0 if female
Age	years
Income	R$
Education	1.No education; 2.Uncompleted fundamental school; 3.Completed fundamental school; 4.Uncompleted high school; 5.Completed high school; 6.Uncompleted University/College; 7.Completed University/College; 8.Graduate Program
Victim of robbery	1 if you've been the victim of robbery; 0 Otherwise
Subject Prob.	$\in (0,1)$
Perception Patrol	1.Always; 2.Often; 3.Sometimes ; 4.Rarely; 5.Never
Willingness to pay	R$/month

Fonte: Elaborated by the Authors

Table 2: Sample Description - Total

Variable	Mean	Std. dev	Min	Median	Max	NA	N
Sex	0.4466	0.4972	0	0	1	0	3784
Age	39.4519	16.8278	16	37	94	80	3704
Income	1,488.70	1,524.27	272.50	817.50	10,900.00	137	3647
Education	3.5552	1.6451	1	3	8	0	3784
Victim of robbery	0.2324	0.4224	0	0	1	1	3783
Subject Prob.	0.4920	0.2990	0	0.5000	1	532	3252
Perception Patrol	2.0533	1.2146	1	1	5	10	3774

Fonte: Elaborated by the Authors

Notwithstanding that, we will not enter in this debate[4], and we simply characterize them as ***protesters***. The ***protesters'*** group, 50.48% of them were men, with average age of 41.42 years old and with completed fundamental school level. In this group, the average income was equal to R$ 1,488.90, but 50% of them earned R$ 817.50 or less. Concerning the expectation of victimization and perception of security, 22,74% of them suffered at least one robbery in the last five years and they consider that the probability of being robbed in the next 12 month is about 48,47%, even though that the perception patrol is often. In the CV's literature, the standard procedure for dealing with this group is to remove them from the sample and proceed to estimation the maximum willingness to pay (Strazzera, Genius, Scarpa, and Hutchinson 2003). However, Strazzera, Genius, Scarpa, and Hutchinson (2003) states that this procedure is valid only when both groups are similar, since if this is not the case, selection bias will pop up.

We compared the empirical distributions for both protesters and those who are willing to pay[5] a positive amount of money and are quite similar. Thus, ***protesters*** and tthose who are willing to pay are quite homogeneous, which indicates that the estimates of willingness to pay using only the second group should not be affected by selection bias (Strazzera, Genius, Scarpa, and Hutchinson 2003). Thus, we remove the group of ***protesters*** from the sample in order to estimate the cost of robberies. Table 3 shows the characteristics of those who are willing to pay to maintain the crime's reduction

[4]For details, see Jorgensen, Syme, Bishop, and Nancarrow (1999)

[5]All tables can be obtained upon request.

program.

Table 3: Sample description - Willing to Pay

Variable	Mean	Std. dev	Min	Median	Max	NA	N
Sex	0.3759	0.4845	0	0	1	0	1708
Age	37.0121	15.6586	16	34	94	54	1654
Income	1,488.45	1,488.40	272.50	817.50	10,900.00	53	1655
Education	3.6089	1.5976	1	4	8	0	1708
Victim of robbery	0.2384	0.4262	0	0	1	1	1707
Subject Prob.	0.5007	0.3008	0.0100	0.5000	1	230	1478
Perception Patrol	2.0235	1.1987	1	1	5	4	1704

Fonte: Elaborated by the Authors

Table 4 shows the frequency distribution of willingness to pay. Of the total of 1,708 respondents who answered that they would accept to pay some amount for maintaining the reduction of robberies crimes, 70 did not know/ did not want to inform a value from those presented in the payment card. Thus, remaining 1,638 observations. The columns ***Cumulative frequency*** and ***Survival probability*** in table 4 indicate, respectively, the number of persons and the percentage of the sample that is willing to pay at least the indicated value. Thus, it can be seen that 990 person, equivalent to 60.40%, are willing to pay at least R$ 10 for the maintenance of combating robbery crimes program.

Table 4: Willingness to pay frequency distribution

WPT	Frequency	Cumulative frequency	Survival probability
1	212	1638	1.0000
5	428	1426	0.8706
10	460	998	0.6093
15	159	538	0.3284
25	173	379	0.2314
50	123	206	0.1258
75	12	83	0.0507
100	38	71	0.0433
150	8	33	0.0201
+150	25	25	0.0153

Fonte: Elaborated by the Authors

One can also notice that as the value of willingness to pay increases, fewer people will be willing to pay this amount!

From this empirical distribution of willingness to pay, it was estimated, non parametrically, the maximum willingness to pay[6]. We estimated the value of R$ 17.44 as the average monthly value or R$ 173.28 per year, as the value that each household would be willing to contribute to reduce by 50% the number of robberies in the city of Fortaleza. Thus, multiplying this value by the total amount of household in Fortaleza, that according to de Geografia e Estatística (2012) is 709,952 households, we estimated the total value of willingness to pay in the amount of approximately R$ 123.02 million per year. Finally, considering that the number of robberies in Fortaleza in 2011 was equal to 33.240[7],

[6] We consider only who response that he would willing to pay more than R$ 1.00 and equal or less than R$ 100.00 per month

[7] Considering only robberies informed to the public security authorities. Source: SSPDC-CE

we have that the implicit value of a statistical robbery[8] is equal to R$ 7,402.03, that is the cost to society of a robbery. However, this non parametric estimation is not the ideal procedure to estimate the maximum willingness to pay, once is expected that the individual characteristics influence the amount that the individual is willing to pay. So, in the next section will be present a parametric model to estimate the maximum willingness to pay for maintain the program for reduce robberies.

3 Econometric Model

Our objective is to build a contingent valuation model to assess the willingness to pay for a first-order stochastic improvement on the odds of being robbed in the city of Fortaleza, Brazil when subjective expectations about the risk is available. Since our data sets come from the same urban space, spatial effects should also be considered. The random vector (R, M, X), where $R \in \{0, 1\}$ is a binary indicator if a shock did not occur or did occur, $M \in \mathrm{R}_+$ measures shock's monetary cost (tangible and intangible costs), $X \in \mathrm{R}^K$ a vector of individual and/or state-specific characteristics. $\theta \in \{0, 1\}$ is an indicator of ***status-quo*** situation or alternative status to be achieved with transfers.

We define four "objective" distribution functions. $P_{R,M,X}(r, m, x) \equiv Prob(R \leq r, M \leq x, X \leq x)$, the distribution function of (R, M, X). Accordingly, the conditional distributions $P_{R,M|X}(r, m|X = x) \equiv Prob(M \leq m, R = r|X = x)$, $P_{M|R,X}(m|R = r, X = x) \equiv Prob(M \leq m|R = r, X = x)$, and $P_{R|X}(r|X = x) \equiv Prob(R \leq r|X = x)$ are defined. Index individuals by $i \in \{1, 2, \cdots, n\}$. We define, as well, four "subjective" distribution functions, say, $P^i_{R,M,X}(r, m, x)$, $P^i_{R,M|X}(r, m|X = x)$, $P^i_{M|R,X}(m|R = r, X = x)$, $P^i_{R|X}(r|X = x)$

Hypothesis 1. *The values for $P_{R,M,X}(r, m, x)$, $P_{R,M|X}(r, m|X = x)$, $P_{M|R,X}(m|R = r, X = x)$, $P_{R|X}(r|X = x)$ exist and are well defined for any $\theta \in \{0, 1\}$ and $i \in \{1, 2, \cdots, n\}$.*

Hypothesis 2. *$P^i_{R,M,X}(r, m, x)$, $P^i_{R,M|X}(r, m|X = x)$, $P^i_{M|R,X}(m|R = r, X = x)$, $P^i_{R|X}(r|X = x)$ exist and are well-defined for any $\theta \in \{0, 1\}$ and $i \in \{1, 2, \cdots, n\}$. Also, except for $P^i_{R|X}(r|X = x)$, the distribution function are the same across individuals and equal to its respective objective distribution.*

Hypothesis 3. *Except for $P^i_{R|X}(r|X = x)$, the distribution functions are homogenous across individuals and equal to its respective objective distribution.*

With a slightly abuse of notation, our basic random set up is described by the following vector $\left(P^\theta_{R,M,X}, P^\theta_{R,M|X}, P^\theta_{M|R,X}, P^{\theta,i}_{R|X}\right)$, for all $\theta \in \{0, 1\}$ and $i \in \{1, 2, \cdots, n\}$.

For each $\theta \in \{0, 1\}$, any individual $i \in \{1, 2, \cdots, n\}$ is endowed with an indirect utility function given by $V_{i,\theta} = V(y_i, \theta)$. Where y_i is sure amount of money and $\theta \in \{0, 1\}$ is an indicator of ***status-quo*** situation or alternative status to be achieved with transfers. Two quantities of interests are:

$$\mathrm{E}\left(V_{i,0}\right) = V(y_i - m, 0)Pr^0_{M|R,X} \times Pr^{0,i}_{R|X} + V(y_i, 0)(1 - Pr^{0,i}_{R|X}) \tag{3}$$

$$\mathrm{E}\left(V_{i,1}\right) = V(y_i - s_i - m, 1)Pr^1_{M|R,X} \times Pr^{1,i}_{R|X} + V(y_i - s_i, 0)(1 - Pr^{1,i}_{R|X}) \tag{4}$$

For pragmatic reasons, we assume that each individual is risk neutral and assume a linear functional form for his/her indirect utility function.

[8]To obtain this value just divide R$ 123.02 million by 16,620, the last one being the number of robberies avoided

Hypothesis 4. *The indirect utility function for each* $\theta \in \{0,1\}$*, any individual* $i \in \{1,2,\cdots,n\}$ *is parametrized as* $V(\widetilde{y_i},\theta) = \beta\widetilde{y_i} + \alpha_\theta X_i + \epsilon_{i,\theta}$.

We also assume that the distribution of shock's size is independent from the occurrence of the shock, say R, and observed heterogeneity, X. Also, for simplicity, the expected value of size of the shock depends only linearly on individual income.

Hypothesis 5. $Pr^0_{M|R,X} = Pr^1_{M|R,X} = P(M)$*, and* $\overline{M} = \tau_1 + \tau_2 Y$.

From Equations (3) and (4), have:

$$\beta\left(y_i - mP(M)\right)Pr^{0,i}_{R|X} + \beta y_i\left(1 - Pr^{0,i}_{R|X}\right) + \alpha_0 X_i + \epsilon_{i,0} \tag{5}$$

$$\beta\left(\left(y_i - s_i - mP(M)\right)Pr^{1,i}_{R|X} + \beta(y_i - s_i)\left(1 - Pr^{1,i}_{R|X}\right) + \alpha_1 X_i + \epsilon_{i,1} \tag{6}$$

Note, however, that the change in ***status-quo*** is a change on $P^{i,\theta}_{R|X}(r|X=x)$. In fact, it is easy to see that $P^{i,1}_{R|X}(r|X=x) \geq_{FSD} P^{i,0}_{R|X}(r|X=x)$, where $\geq_{FSD}$ means first-order stochastic dominance[9]: note that $Pr^{1,i}_{R|X} = k \times Pr^{0,i}_{R|X}$, where $k \in (0,1)$, the payoffs are $\{-\overline{m}, 0\}$, and $Pr^{\theta,i}_{R|X} = Prob(R = -\overline{m}|X)$, for $\theta \in \{0,1\}$. See, Figure (1). Now we are able to develop the expression for the willingness to pay by equating Equations (5) to (6), and solving for s_i.

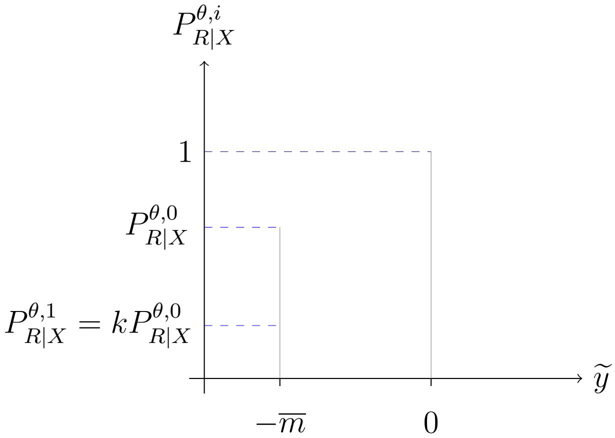


Figure 1: First Order Stochastic Dominance

$$s_i = \left(Pr^{0,i}_{R|X} - Pr^{1,i}_{R|X}\right)\overline{m} + \frac{(\alpha_1 - \alpha_0)}{\beta}X_i + \frac{(\epsilon_{i,1} - \epsilon_{i,0})}{\beta} \tag{7}$$

First note that the expression for the willingness to pay s_i depends on the difference on the expected value of the shock between the ***status quo*** and the new situation, say, $\left(Pr^{0,i}_{R|X} - Pr^{1,i}_{R|X}\right)\overline{m}$, as well as it depends on observed and unobserved heterogeneity. In fact, as expected given a risk neutral agent, the income does not have a bite. However, in the sequel, we show that the shock value is a function of the cross-product of income and subjective probability of robbery, say, $Pr^{0,i}_{R|X}y_i$! Hence, the final expression for s_i is dependent on y_i, individual income.

Remember that $Pr^{1,i}_{R|X} = k \times Pr^{0,i}_{R|X}$, and $\overline{m} = \tau_1 + \tau_2 y_i$. Defining $\alpha \equiv \frac{(\alpha_1 - \alpha_0)}{\beta}$, and $\epsilon_i \equiv \frac{(\epsilon_{i,1} - \epsilon_{i,0})}{\beta}$, and $Z_i \equiv (1-k)Pr^{0,i}_{R|X}$, $W_i \equiv Z_i y_i$ we get the estimable equation, where, with no loss of generality, right hand side variable appears in logarithmic form:

[9]Remember that the counterfactual proposed by question 105 in Carvalho (2012) was phrased like ... *to cut in half the occurrence of personal robbery in Fortaleza ...*

$$\ln(s_i) = \ln(\tau_1 Z_i + \tau_2 W_i + \alpha X_i) + \epsilon_i \tag{8}$$

Where, $\epsilon_i \sim N(0, \sigma^2)$. Approximating the left hand side of Equation (8) by a first order Taylor's expansion (Note that the full Taylor's approximation is $\ln(x) = (x-1) - \frac{(x-1)^2}{2} + \frac{(x-1)^3}{3} - \frac{(x-1)^4}{4} \cdots$, as long as we re-scale monetary values s_i to belong to the interval $(-1, 1]$ actually close to 1, we get:

$$\ln\left(\frac{s_i}{\theta}\right) = \ln\left(\frac{\tau_1}{\theta} Z_i + \frac{\tau_2}{\theta} W_i + \frac{\alpha}{\theta} X_i\right) + \epsilon_i \tag{9}$$

Where $\theta \in (\min(s_i), \max(s_i))$. Assuming that X_i has an intercept whose parameter is $\frac{\alpha_{intercpt}}{\beta}$:

$$\ln(s_i) = \left(\frac{\alpha_{intercpt}}{\beta} + \ln(\theta) - 1\right) + \frac{\tau_1}{\theta} Z_i + \frac{\tau_2}{\theta} W_i + \frac{\alpha}{\theta} X_i + \epsilon_i \tag{10}$$

Before we proceed it is worth noting that models that incorporate willingness to pay for first-order stochastic dominance improvements on risks is a quite new endeavor. In fact, there are only two papers we are aware of, say, Cameron, DeShazo, and Stiffler (2010) and Cameron and DeShazo (2013), that build on this topic. Their approach are different from ours, however. So, Cameron and Huppert (1989) proposes that contingent valuation data sets obtained through payment cards' method can be analyzed parametrically by means of maximum likelihood models with data in intervals. They suggest that when an agent chooses a value in payment card, say t_{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 t_{u+1i}. Therefore, the probability that the agent choose to pay the t_{ui} value is equal to the probability that the true willingness to pay it is in the range defined by t_{ui} and t_{u+1i}.

$$P(t_{ui}) = P(t_{ui} \leq s < t_{u+1i}) \tag{11}$$

Thus, it is possible rewrite 11 as:

$$P(t_{ui}) = P(log(t_{ui}) \leq log(s_i) < log(t_{u+1i})) \tag{12}$$

By equation 10, we have that s has mean μ and standard deviation σ. Then, define μ as:

$$\mu = \left(\frac{\alpha_{intercpt}}{\beta} + \ln(\theta) - 1\right) + \frac{\tau_1}{\theta} Z_i + \frac{\tau_2}{\theta} W_i + \frac{\alpha}{\theta} X_i \tag{13}$$

we can standardize each pair of interval thresholds and state that:

$$P(t_{ui}) = P\left(\frac{log(t_{ui}) - \mu}{\sigma} \leq z_i < \frac{log(t_{u+1i}) - \mu}{\sigma}\right) \tag{14}$$

where z_i is the standard normal random variable. The probability above can be rewritten as the diference between two standard normal cumulative densities. Then, let Φ denote the cumulative density function of a standard normal variable, it follows that:

$$P(t_{ui}) = \Phi\left(\frac{log(t_{u+1i}) - \mu}{\sigma}\right) - \Phi\left(\frac{log(t_{ui}) - \mu}{\sigma}\right) \tag{15}$$

Finally, Cameron and Huppert (1989) assert that the joint probability density function for n independent observation can be interpreted as a likelihood function, defined over the unknown parameters γ e σ. Thus, the log-likelihood function takes the following form:

$$logL = \sum_{i=1}^{n} log\left[\Phi\left(\frac{log(t_{u+1i}) - \mu}{\sigma}\right) - \Phi\left(\frac{log(t_{ui}) - \mu}{\sigma}\right)\right] \tag{16}$$

From the maximization of 16, we find the optimal values of γ e σ, with values of γ showing the impact of individuals characteristics on the choice of the value of willingness to pay. From these estimated values of γ e σ, it is possible estimate mean and median WTP, as shown below:

$$\text{Mediana DAP} = exp\left(\left(\frac{\alpha_{intercpt}}{\beta} + \ln(\theta) - 1\right) + \frac{\tau_1}{\theta}Z_i + \frac{\tau_2}{\theta}W_i + \frac{\alpha}{\theta}X_i\right) \tag{17}$$

$$\text{DAP Média} = exp\left(\left(\frac{\alpha_{intercpt}}{\beta} + \ln(\theta) - 1\right) + \frac{\tau_1}{\theta}Z_i + \frac{\tau_2}{\theta}W_i + \frac{\alpha}{\theta}X_i\right) exp(\sigma/2) \tag{18}$$

This two measures provide what we call a global value for WTP. However, we expect that spatial heterogeneity has an important role in the relation between the choice of how much the agent wants to pay and his characteristics. This means that values of γ can be different, which would make individual WTP values differ all over the city. A plausible explanation for this would be that individuals through different neighborhoods meet different levels of criminality, whether observed or not by police authority[10], which would lead their willingness to pay to be different. Thus, in order to handle this issue of spatial heterogeneity we use geographically weighted regression technique (GWR) to estimate a local WTP in such a way that will be possible identify in which regions the WTP will assume higher values. Next section, presents the GWR model.

4 A "Local" Econometric Model

According to Almeida (2012), analyzing only the average or global response of a phenomenon may not be useful or convenient, since socioeconomic phenomena are not likely to be constants through regions. Fotheringham, Brunsdon, and Charlton (2003) refer to this situation as spatial non-stationarity and claim that any relationship that is non-stationary over space is not well represented by a global statistic and, indeed, this global value may be very misleading locally.

Fotheringham, Brunsdon, and Charlton (2003) affirm that there are several reasons to expect that a relationship vary over space. Among possible explanations we can cite sample variations, mis-specification and, most important, there might be some relationships that are intrinsically different across space. In the last case, it is suggested that there are spatial variations in peoples' attitudes or preferences or there are different administrative, political or other contextual issues that produce different responses to the same stimuli over space.

In the case of the object of study of this article, it is a stylized fact that crime distribution is heterogenous across space. In big cities, like Fortaleza (the fifth largest city in Brazil with an area of 313 square kilometers, boasting one of the highest demographic densities in the country, say, 8,001 per km^2), occurrences robbery are concentrated on richer areas of the city, leading to formation of clusters of criminality in these areas. Due to this heterogeneous distribution, we expected that individuals' reactions to crime be also heterogeneous. So, we expect that an individual who lives in a region with high rates of criminality to have a different behavior than an individual who lives in low crime prone regions. Thus, unlike classical models of spatial dependence, here we not expect that individuals can influence each other willingness to pay, but we expected that different individuals have different factors that influence his willingness to pay. So, a variable that can influence the willingness to pay for individual i maybe have no influence on individual j, or have more or less influence. In this way, a local model is necessary to estimate this relationship.

The geographically weighted regression (GWR) is a method that extend the traditional regression framework by allowing the estimation of local parameters rather than global parameters (Fotheringham, Brunsdon, and Charlton 2003). This method generates a sequences of regressions

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

estimated for each region, using subsamples of the data, weighted by distance (Almeida 2012). Subsamples are created from the regression or calibration point, that is the reference point for the parameters estimation for the region i. From this point, each observation belonging to the sample is weighted according to its distance to the calibration point. Close observation have a higher weight, while more distant observations have a lower weight (Almeida 2012).

The weights used for the creation of these subsamples is taken by the spatial kernel function. According Almeida (2012), 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 between these two regions, which is inversely related to geographic distance (w_{ij}) (Almeida 2012).

Fotheringham, Brunsdon, and Charlton (2003) classifies the spatial kernel functions in two groups: the fixed kernels and the adaptive kernels. In the fixed kernels, the 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 be and hence using information in excess, turn estimates biased. On the other hand, in regions where data are scarce, the kernels are smaller than they need be to estimate the parameters reliably (Fotheringham, Brunsdon, and Charlton 2003). The adaptive kernels reduce both problems by making the bandwidth (b) greater or smaller depending on data density in the area. We use the fixed[11] gaussian[12] kernel, defined by equation 19:

$$w_{ij} = exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right) \tag{19}$$

Due to the aforementioned problems the choice of the bandwidth (b) must be made so that try to solve the trade-off between bias and efficiency. To this end, to avoid arbitrary choices, the bandwidth is estimated using the data (Almeida 2012). There are several techniques[13] used to determine the optimal value of the bandwidth. In this paper, we use the cross-validation technique. It consists in minimizing the following function, represented by equation 20:

$$CV = \sum_{i=1}^{n} \left(y_i - \hat{y}_{\neq i}(b)\right)^2 \tag{20}$$

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, Brunsdon, and Charlton (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:

$$W(u_i, v_i) = \begin{bmatrix} w_{i1} & 0 & \cdots & 0 \\ 0 & w_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_{in} \end{bmatrix} \tag{21}$$

where w_{in} is the weight attributed to the point n in the model calibration in the regression point i, obtained through spatial kernel function. Thus, from the model show in equation 16, the local

[11] For computational reason, we will use adaptive kernel in a subsequent paper

[12] For other types of kernel functions, see, among others, Fotheringham, Brunsdon, and Charlton (2003) e Almeida (2012).

[13] For more details, see Fotheringham, Brunsdon, and Charlton (2003).

model can be specified by the following weighted maximum likelihood function, represented by the equation 22:

$$logL = \sum_{i=1}^{n} W(u_i, v_i) log \left[\Phi \left(\frac{log(t_{u+1i}) - \mu}{\sigma} \right) - \Phi \left(\frac{log(t_{ui}) - \mu}{\sigma} \right) \right] \tag{22}$$

From the above equation, are estimated parameter sets for each n points. Next section presents results of estimation for both global and local models.

5 Results

5.1 Results from the Global Model

Table 5 shows the results of the estimation of the global model represented by Equation 16. All parameters are statistically significant. The sign of estimates indicate the effect on willingness to pay. All variables, except ***Age***, show positive sign. The negative sign of variable ***Age*** indicate that older people tends to pay less to reduce crime than young people, indicating that older people have a greater feeling of security than young people. As to variables ***Sex,Education*** the positive sign indicate that men and more educated people tends to pay more for reduce the risk of being robbed. Finally, as to variables of perception and experience of victimization (variable ***Perception patrol*** is measured in decreasing order), the lower the perception of patrolling the greater the willingness to pay to reduce the number of robberies, and people who was ***Victim of robbery*** tends to pay more to prevent such experience again.

Table 5: Estimates- Parametric Maximum Likelihood

Varable	Estimate	Stad. Dev.	t	p-value
(Intercept)	2.3949	0.1024	23.3750	0.0000
I(Subject Prob. * Income)	0.0002	0.0000	4.7072	0.0000
Sex	0.1897	0.0477	3.9738	0.0000
Age	-0.0034	0.0016	-2.0946	0.0362
Education	0.0466	0.0160	2.9058	0.0036
Perception patrol	0.0520	0.0196	2.6559	0.0079
Victim of robbery	0.0926	0.0550	1.6818	0.0926
σ	0.7299	0.0167	43.6735	0.0000
log-likelihood = -1851.53				
Newton-Raphson maximization, 4 interations				

Fonte: Elaborated by the authors

Variable ***I(Subject Prob. * Income)*** deserve a special attention. The positive sign of this variable shows that the higher is the income and the subjective probability of being robbed the higher will be the willingness to pay for reduce the risk of being robbed. On the other hand, when this variable is multiplied by θ we have the fraction, in average, of the income robbed in each robbery. This value is equal approximately to 0.0415. So, in each robbery, approximately 4,15% of the income is robbed. Multiplying this value by average income we have a value of R$ 61,38 per robbery.

In next table 6, the values of estimated WTP, as defined by equation 17, are presented.
The average WTP estimated from global model is equal to R$ 23.35 per month/household, a higher value of R$ 5.91 than the estimated value of non parametric form, which was only R$ 17.44. Thus, if the government decided to implement a monthly tax in this value, would be possible to raise, per

Table 6: Results of WTP(R$) from the global parametric model

Variável	Estimativa	Desvio Padrão	Inter. Conf.
Mean	23.35	6.12	22.98 - 23.72
Median	16.21	4.25	15.95 - 16.47

Fonte: Elaborated by the authors

year, R$ 280.20 per household, which would generate an average tax revenue of about R$ 198.92 million per year, equivalent to approximately 20.63% of the amount spent on public security in the state of Ceará in 2011[14]. Assuming a worst case scenario, using as a benchmark the median value of WTP of R$ 16.21 per month/household, we have a value of R$ 194.52 per year/household. In this case, the annual tax revenue in Fortaleza would be approximately R$ 138.09 million, equivalent to 14.32% of spending on public security in 2011.

Now, considering the damage of robberies to society, in first scenario, where the WTP was estimated in R$ 23.35, it is estimated the implicit value of a statistical robbery approximately equal to R$ 11,969 per robbery avoided. Considering the second scenario, where was utilized the value of median WTP equal to R$ 16.21, the value of a statistical robbery was estimated approximately equal to R$ 8,310 per crime avoided. Next section presents results from the local model.

5.2 Results from the Local Model

As discussed early, considering only the average or global response of a phenomenon may not be useful or convenient, see (Almeida 2012). In this way, we estimated[15] a local model specified by Equation 22. First, we present the estimated model with a fixed bandwidth. The cross-validation technique[16] pointed us a bandwidth (b) of 3,5399 km with a CV score of 578.2882. Table 7 shows the estimates[17] under this value of b.

Table 7: Estimates for the Local Model - GWR - Fixed bandwidth

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
(Intercept)	1.8830	2.3860	2.4410	2.4170	2.4840	2.6620
I(Subject Prob. * Income)	0.0001	0.0002	0.0002	0.0002	0.0003	0.0004
Sex	0.0861	0.1285	0.1814	0.1887	0.2303	0.3861
Age	-0.0085	-0.0057	-0.0044	-0.0039	-0.0030	0.0052
Education	0.0095	0.0405	0.0521	0.0474	0.0553	0.0708
Perception patrol	-0.0466	0.0414	0.0483	0.0524	0.0597	0.1309
Victim of robbery	-0.2231	0.0783	0.0912	0.0994	0.1269	0.3660
σ	0.6180	0.7073	0.7216	0.7306	0.7661	0.8153

Estimation using gaussian fixed bandwidth equal to 3.539923 Km

Fonte: Elaborated by the Authors

Now, in contrast with global model, we have a parameter distribution for each variable. In this type

[14]According to the de Segurança Pública (2012), the amount spent on public security in the state of Ceará in the year 2011 was R$ 964,095,556.61.

[15]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)).

[16]This computation lasted approximately 1 day, in a Intel Core i5-2400 CPU 3.1 GHz 4,00 GB RAM.

[17]This computation requires approximately 3 hours, requiring much less time than the choice of bandwidth.

of model, the tabular representation is not a good deal. Although we should show 8 figures (one for each of the 8 variable appearing in Table 7), for pragmatic reasons we present four, say, *Subject Prob. * Income*, *Sex*, *Age*, and *Education*. So we present this result in Figures (2), (3), (4), and (5). For example, in west region of the city of Fortaleza, the impact of variable *Subject Prob. * Income* is greater than in east regions. The same pattern occurs for variables *Sex* and *education*.

Figure 2: Estimated parameters spatial distribution - Subject Prob. * Income

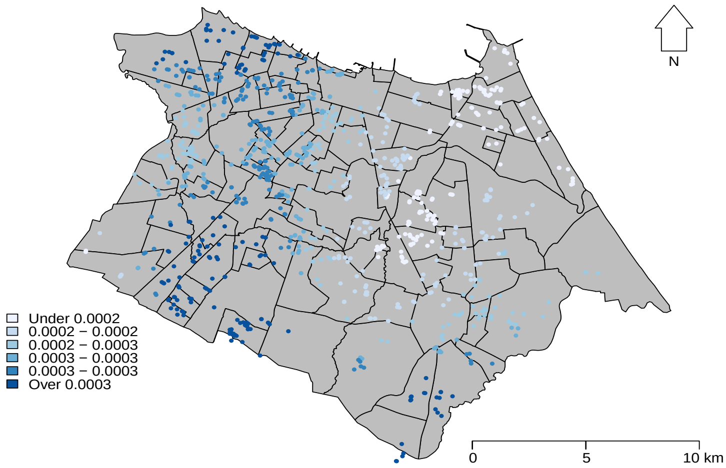


Figure 3: Estimated parameters spatial distribution - Sex

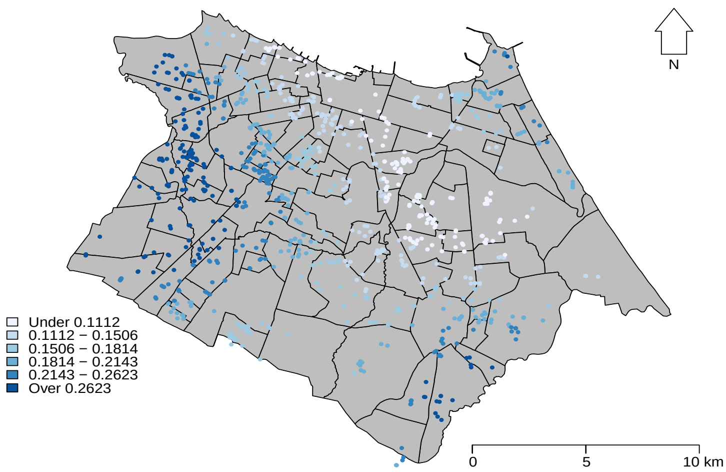


Figure 4: Estimated parameters spatial distribution - Age

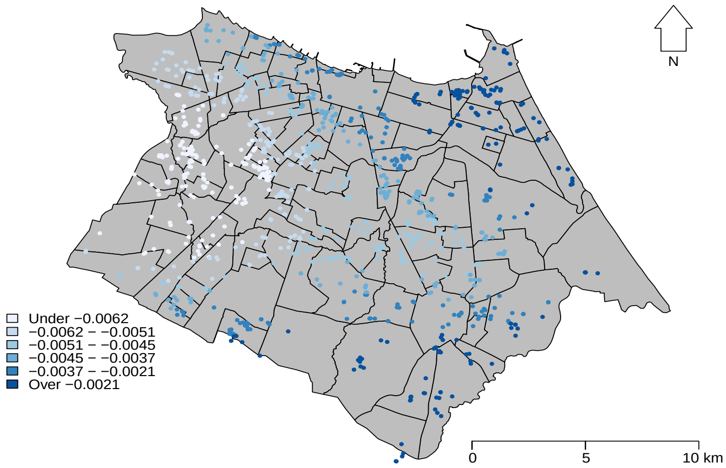
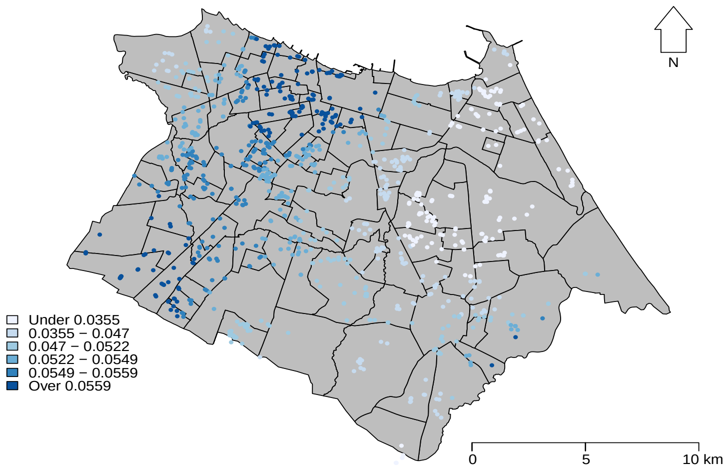


Figure 5: Estimated parameters spatial distribution - Education



For variable *Age*, the impact is grater is east regions. Note that with this parameter distribution, it is possible to create a willingness to pay's distribution. In order to do that we plug in the parameter vector into each individual's vector of observations and calculate the expected willingness to pay and sort them into six classes. Figure 6 show us the spatial distribution of willingness to pay. In this figure, we see that the highest values of estimated willingness to pay is concentrated in central region of the city, in the prime area. This area is populated by rich people and is the area where is concentrated the greatest amount of robberies in the city, which can explain this concentration of greatest values of willingness to pay.

Figure 6: Willingness to Pay - Spatial Distribution

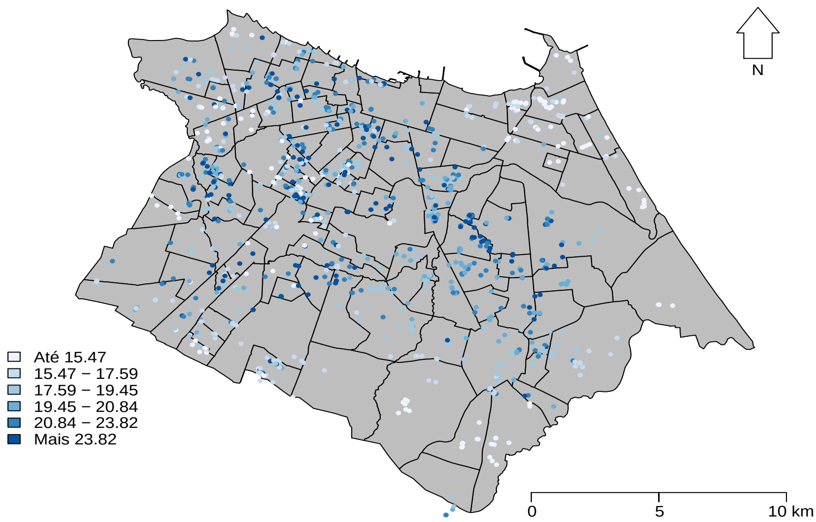
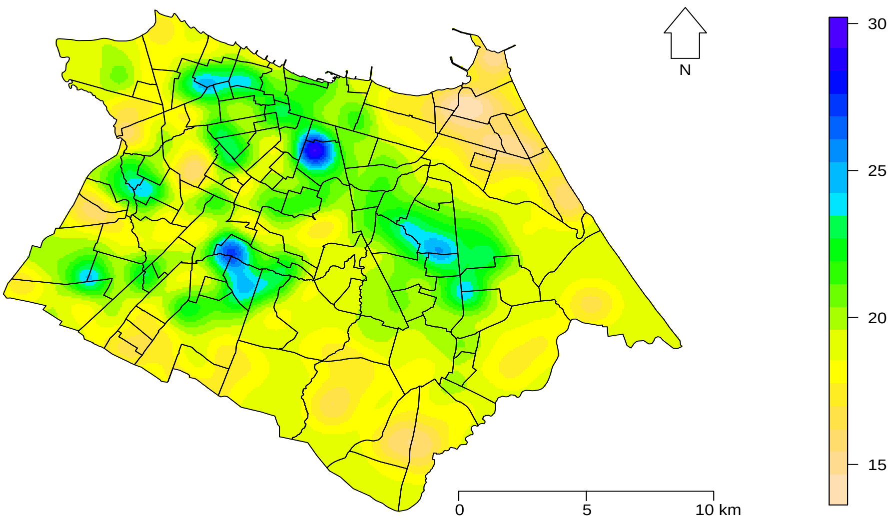


Figure 7: Willingness to Pay - Kriging Surface



Before we compare this values with those from the global model, we will construct a interpolated surface to predict the willingness to pay for entire city of Fortaleza. To do that, we will use the Ordinary Kriging technique[18]. In this map (see, Figure 7), we can see that the border of the city

[18]For more details of this method, see, among others Druck, Carvalho, Câmara, and Monteiro (2004) and Bivand, Pebesma, and Gómez-Rubio (2008)

has a low willingness to pay, represented by lightening colors. Although in this area the crime rate is extremely high, the types of crimes which occurs are crimes against life, while robberies are less common. Furthermore this area is populated by low income people, which have little to be stolen. On the other hand, in dark areas, we have a high willingness to pay. In this area, the reverse pattern occurs. There are a high level of crimes of robberies and a low level of crimes against life. Moreover, in this the population is composed by high income people, that have more to be stolen. Thus, this heterogeneity in spatial distribution of crime and income may be a explanation to the spatial heterogeneity in willingness to pay distribution.

Comparing the values in local model with those from the global model, we can see that in almost whole city the willingness to pay is lower then the average global willingness to pay. Therefore, in case of implementing a tax, if the value set is equal to R$ 23.35, many people looses welfare, once the value that they will pay is higher than that they want to. On the other hand, there are many people that want to pay more than they will pay, so the government will loss funds of this group. So, a flat tax to finance crime reductions is not efficient. A first degree price discrimination (see, (Varian 2006)), where each unit of a goods must be sold to an individual at his/her reservation price or his/her maximum willingness to pay, might be a better solution, although politically difficult. Therefore an efficient and ideal way might be to determine the tax value by areas, setting it to the estimated maximum willingness to pay in that area.

6 Final Considerations

This paper sought to apply a new methodological approach to estimate willingness to pay in a large urban center in Brazil that includes spatial effects in the analysis. We constructed a theoretical model that explains the determinants of willingness to pay from the random utility model for a first-order stochastic improvement on the odds of being robbed in the city of Fortaleza, Brazil when subjective expectations about the risk is available. We showed that the determinant factors explaining willingness to pay in the city of Fortaleza are ***Subject Prob*Income***, ***Sex***, ***Age***, ***Education***, ***Perception patrol*** and ***Victim of robbery***.

From global model, we estimated mean willingness to pay equal to R$ 23.35 per month/household as the value that representative citizen of Fortaleza would be willing to pay for reduce in 50% the amount of robberies in the city. From this value, we calculated in approximately R$ 198.92 million the total cost to society, equal to 20.63% of the total amount spent on public security in the state of Ceará in 2011. We also estimated the WTP per robbery avoided equal to R$ 11,969.

In our greatest contribution, the local model, utilizing a fixed gaussian kernel function with a fixed bandwidth approximately equal to 3.5 km, we estimated a geographically weighted regression with interval regression that, to the best of our knowledge, is the first study to do so. In local model, we showed that in almost whole city, the willingness to pay estimated in local model is lower than one estimated in global model and that there is island where this value is greater. So, in case of implementation of a tax, the most efficient procedure is discriminate the tax according to the area.

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

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