Does a Longer Commuting Time Increases the Probability of Being Victim of Urban Violence? Evidence from Brazilian Metropolitan Regions

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Abstract

Empirical evidence about the influence of exposure to public spaces on victimization strongly support the routine activities theory but, maybe reflecting the difficult of available data, specific evidence about the influence of the commuting on probability of victimization is not abundant. In this paper, we analyze this relationship using a large nationally representative cross-section sample of Brazilian individuals for 2009, using propensity score matching techniques to create counterfactuals and performing robustness checks and implementing a simulation-based sensitivity analysis that support a causal interpretation of the results. We find that individuals with more than one hour of commuting have an overall 2.1% increase in the probability of being victim of robbery, with no robust impact on theft. Also, following the exposure literature we find larger effect on the probability of robbery victimization on women when compared with men, 2.5% and 2.2% respectively.

Keywords: commuting; urban violence ; treatment effect .

JEL Classification: C21, K49, .

Abstract

A evidência empírica sobre a influência da exposição a espaços públicos na vitimização apoia firmemente a teoria das atividades rotineiras mas, talvez refletindo a dificuldade de disponibilidade de dados, evidências específicas sobre a influência da mobilidade pendular na probabilidade de vitimização não é abundante. Neste artigo, analisamos esta relação usando uma grande amostra nacionalmente representativa de seção transversal de indivíduos brasileiros para 2009, utilizando técnicas de pareamento via escore de propensão para criar contrafactuais, realizando testes de robustez e fazendo um análise de sensibilidade que suportam uma interpretação causal dos resultados. Encontramos que os indivíduos com mais de uma hora de comuting *têm um aumento de 2.1% do total na probabilidade de ser vítima de roubo, sem impacto robusto no furto. Além disso, após a literatura sobre exposição, encontramos efeito maior sobre a probabilidade de vitimização por roubo em mulheres quando comparadas com os homens, 2.5% e 2.2%, respectivamente.*

Keywords: commuting; violência urbana; efeito do tratamento.

1 Introduction

With around 85% of its population living in urban areas in 2010, according to the information of last Brazilian Demographic Census, the process of urbanization in Brazil is a very advanced one. This advanced stage agglomeration of people in the cities certainly brings a game of implications and challengers for social lives in Brazilian in very different dimensions, from the possibilities of economic gains due to agglomeration economies, to the necessity of urban planning and solutions for questions of mobility and pollution, for example. Nevertheless, due to the cost their represent to Brazilian urban centers and their direct influence on urban life quality, the problems of urban violence and of long commuting time experienced in Brazilian metropolitan regions are certainly among the most relevant ones.

As registered by United Nation Office on Drugs and Crimes (UNODOC, 2012), Brazil is one of the most violent country in the world, with homicide rates around 27.1 (homicides per one hundred thousand people) in 2011, the third highest rate among Latin America countries (behind of only Colombia and Venezuela). This situation, in fact, reflect a general situation of high violence related to other kinds of crime in the country; as related to the violence associated to robbery, for example, the numbers of UNDOC (2012) for 2010 put Brazil, with rates (occurrences per one hundred thousand) of robbery and of theft around 554.5 and 709.3, respectively, again among the three most violent Latin American Countries. The situation is even worse in Brazilian biggest cities, where the homicide rates can be easily around 100 homicides per one hundred thousand, according to information of Ministry of Health (DATASSUS, 2013) and the chance of victimization by robbery or thief are substantially higher in its metropolitan regions. According to the numbers of the annually Brazilian household survey for the year of 2009 (PNAD 2009), for example, the proportion of people of 10 years old or more that had been victim of robbery or thief was 2.3% for rural areas, but around 8.1% for urban areas and 10.4% for Brazilian metropolitan regions.

But the problem of urban violence is neither the only substantive urban problem of Brazilian big urban centers, nor it is dissociated to other urban problems in these centers. Besides the risk of being victim of urban violence, visitors or inhabitants of Brazilian metropolitan regions must face with the problem of low mobility in these cities. The very bad quality of public transport together with public indirect subsidies for using individual transport make short distance locomotion a very high time demand action (IPEA, 2013). According to the more recent information of PNAD (PNAD 2012), the average commuting time for the inhabitant of Brazilian metropolitan regions was around 40.8 minutes in 2012, a very high number if compared to metropolitan regions around the world (Pereira and Schwanen, 2013; Silveira Neto et al. 2014). As shown by Silveira Neto et al. (2014), the commuting time, of the metropolitan region of São Paulo is much higher than the one observed for metropolitan regions of New York and Seoul, for example.

Besides of implying waste of potential productive time and lower life quality for the inhabitant of Brazilian metropolitan regions, a longer commuting, by imposing much time of individuals in public environment, has a potential effect on probability of an individual be victim of urban violence. According to sociological theory of routines activities (Mayhew et al. 1974; Cohen and Felson, 1979; Cohen, Kleugel and Land, 1981), in spaces of low or ineffective guardianship, a longer exposure to public spaces creates more favorable conditions for victimization of the individuals. From economic point of view, that empathizes the rational behavior of criminal (Becker, 1968; Heineke, 1978), a longer time in public space reduces the cost of committing crime for the potential criminals: it reduces the time involved in researching for potential victims and simultaneously, by potentially generating more vulnerable situations for the commuter, it reduces the cost of executing the crime. On the other hand, longer commuting time can also implies more precaution by the rational individuals when in public spaces. As these two effects are present in respective of the characteristics of the potential criminals and of other urban specific characteristics, a longer commuting time of one individual can imply higher probability of an individual be victim of violence in Brazilian metropolitan regions.

Empirical evidence about the influence of exposure to public spaces on victimization strongly support the routine activities theory (Cohen and Cantor, 1981; Messener and Blau, 1987; Miethe, Stafford and Long, 1987), but, maybe reflecting the difficult of available data including individual information of both victimization and commuting, specific evidence about the influence of commuting time on probability of victimization is not abundant, although some explicit worry about insurance in public transport (Clarke, 1996). Recent evidences, nevertheless, appear to confirm the above expectation. Wang and Minor (2002), using American census tracks, found an inverse relation between accessibility to jobs and violent crime in the city of Cleveland, Ohio. Lemiux and Felson (2012), using data from National Crime Victimization Survey and American Time Survey, built time adjusted measures of exposure to violent attack[1] and showed that the greater risk occurs during travel between activities, specifically, commuting to work and to school. Messner et al. (2007), using a set of unique data of victimization for the city of Tianjin, China, and after controlling for the influence of set of demographic variables and other life-style variables, showed that more frequent traveling for work out the city increase the risk of being victim of the urban theft.

As for Brazil, some studies found that specific measure of exposure influence on the probability of being victim of urban violence. Beato et al. (2004), for example, found that, for the specific case of the city of Belo Horizonte, the use of public transport has a positive influence on the probability of being victim of theft or robbery. Peixoto, Andrade and Moro (2007), using victimization data for the cities of Rio de Janeiro, Recife, São Paulo e Vitoria, showed that individuals with is daily or weekly outside of home present higher chance of being victims of urban theft. But, to best of our knowledge, none study provided evidence about the influence of a longer commuting time on the chance of being victim of urban violence, neither considered the set of all Brazilian metropolitan regions. Lack of information is surely part of the explanation. of information. Fortunately, the government annually household survey (Pesquisa Nacional por Amosta de Domicilios - PNAD) of the year 2009 extraordinarily contain, along with traditional information about individuals and their families, information about individuals commuting time and victimization (associated to robbery, thief and aggression) contemporaneous experiences.

From this referred database, we note that while the percentages of individuals living in Brazilian metropolitan regions that had been victim of robbery and thief were, respectively, 10.1% and 11.2% for those individuals with commuting timer longer than one hour in 2009, the same percentages were 8.8% and 9.8% for the ones with commuting time up to one hour. These numbers are thus appear consistent with the above relationship between commuting time and the probability of being victim of urban violence.

The main objective of this paper is to investigate the existence of a causal relationship be-

[1]Include rape or sexual assault, robbery, aggravated assault, threat of violence and simple assault.

tween commuting time and the probability of being victim of urban violence for individuals living in Brazilian metropolitan regions, i.e., to determine if a longer commuting time regular implies a higher chance of being victim of urban violence for individuals of these urban centers. In order to obtain this evidence, we use non-experimental methods of matching individuals based on their propensity score (associated to commuting time) and characteristics and the unique characteristics of Brazilian household survey of the year of 2009 that provides simultaneously information about the commuting time and victimization of the individuals.

Our results suggest that there is causal relationship between commuting time and the probability of being victim of urban violence (robbery and thief) in Brazilian metropolitan regions: a longer commuting time implies a higher probability of being victim of urban violence in these referred metropolitan regions, being this violence a robbery or a thief. In addition, the evidence also shows that the influence of a longer commuting on the probability of being victim of urban violence in Brazilian metropolitan regions is stronger for women than for men and this influence of the commuting time on victimization also does not appear explained by the social characteristics of the location of the residence.

In addition to this section, the investigation is structured on more four sections. In the next section, we present a simple economic model based on criminal rationale to formalize the relationship between a commuting time and the chance of being victim of violence in a urban location. In section three, we present our empirical strategy and the database we use during the investigation. The results of the investigation are presented in section four and in section five we present concluding remarks.

2 Victimization and Commuting time under economic perspective: a simple model

From economic point of view, the missing part of the most of victimization approach to the problem of urban violence is that the proposed arguments barely are associated to the structure of incentive of the potential criminals. After all, for the occurrence of a violent crime it is necessary the action of motived people, i.e., people with a positive balance between benefits and costs of the criminal action. Here, we proposed a simple extension of the Becker (1968) based model proposed by Gaviria and Pagés (2002) to capture the influence of commuting time on the individual chance of being victim of a violent robbery or theft. Basically, the model extends Graviria and Pagés (2002) model by considering the influence of commuting time of potential victims on the costs of committing crime and by explicitly recognizing that expected losses of a potential victim of a crime increase with her commuting time because of the longer time of exposure. The extension presents some similar aspects to the proposal extension of Gomes and Paz (2007) but takes explicitly in to account the effects of commuting time on both potential criminal and victims.

Basically, we extend Graviria and Pagés (2002) model by considering the effect of commuting on the expected gain of crime action of potential criminals and on the expected loss of victims. A longer commuting time implies much time of individuals in public envi- ronment and less time at home and this in turn affects both the expected net gains of criminal action and the expected losses for a potential victim. More specifically, on one hand, a longer commuting time of potential victims generally involves the possibility of greater numbers of situations of more vulnerability of the individual, which decreases the cost of committing crime by a potential criminal and thus increases the his expected gains[2]. But, on the other hand, a longer exposure to public spaces associated to longer commuting times also a longer exposure to potential criminals and, thus, must increases expected losses for the potential victims.

The basic structure of the model is the same of Graviria and Pagés (2002). There are N risk neutral individuals in the society previously spliced between potential criminals and victims and there is two stages. In the first stage, citizens, potential victims that differ on their wealthy holdings and on their commuting time, must decide how much to spend in private protection in order to avoid to be victim of robbery or theft. In the second stage citizens are matched with criminals in public space of the city and the potential criminal decides or not to commit crime observing the potential victim's wealth (w), private spending in private protection (e) and commuting time (c). The decision of committing crime is based solely on the expected net pecuniary gains; apart from the victim's wealth (w), the net gains depend on the probability of apprehension, $p(e_i)$, on the parcel of victim's wealthy captured during the action, $\alpha(c_i)$, and on the cost involved with a potential apprehension, F.

As Gaviria and Pagés (2002), we also assume that $p'(e_i) > 0$, i. e., the probability of apprehension increases with the spending with private protection. In addition, in order to reflect more advantage conditions for the criminals associate to a longer commuting time of a potential victims, we also assume that $\alpha'(c_i) > 0$, in other words, that the parcel of the wealthy captured during a criminal action increases with the commuting time of the victim. We also assume that there is not any relationship between individual commuting time and wealth. Fourth, the criminals have complete information about the victims: they observe their victim's wealth, commuting time and know the chance of being apprehended.

From above assumptions, we observe that a criminal will commit a crime against individual i if:

$$(1 - p(e_i)).\alpha(c_i)w_i - p(e_i).F > 0 \tag{1}$$

From condition (1), we note obtain the minimum level of spending in private protection necessary for individual i not be a victim. This corresponds to the level of spending that makes a criminal indifferent about commit or not the crime:

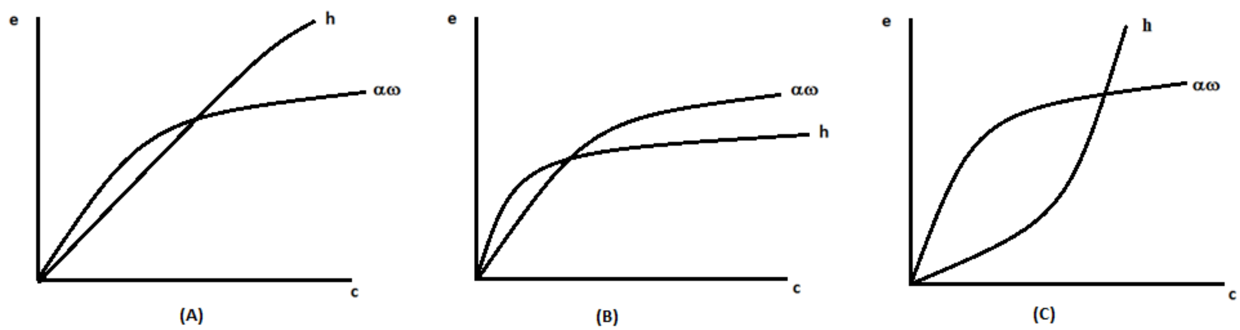
$$h(c_i) = \left[\frac{\alpha(c_i)w_i}{\alpha(c_i)w_i + F}\right].p^{-1} \tag{2}$$

where p^{-1} is the inverse function of p and, thus, associate the probability of apprehension to the level of spending. Of course, the potential victims are interested in spending $h(c_i)$ only if level of spending does not exceeds the expected losses of being victimized, given by $\alpha(c_i)w_i$, in other words, only if $h(c_i) \leq \alpha(c_i)w_i$.

From equation (2), it can be notice that, all else being equal, this level of spending increases with the commuting time of the potential victim, a relationship that just reflect the most favorable conditions to the criminal relative a potential victim with a longer commuting time. More formally:

[2]More specifically, for example, a longer commuting can involve the necessity of using two or more public ways of transport to arrive at the work location and this generally implies different security conditions in waiting for and using the public transportation. This implies that longer commuting time is also associated to lower costs of executing the criminal action by potential robbery criminals.

Figure 1: Private spending in security (e) and commuting time (c).



$$\frac{dh(c_i)}{dc_i} = \frac{F\alpha'(c_i)w_i}{[\alpha(c_i)w_i + F]^2 p'h(i)} > 0 \tag{3}$$

This relationship indicates that, for individual with the same wealth, the longer the commuting time, the higher the minimum spending necessary to avoid being victim of crime. But, because the commuting time also affects victim's expected loss, all else being equal, the model generates a positive association between commuting time and victimization only with additional requirements.

Assuming that the parcel of the victim's wealth a criminal can capture increases in a decreasing rate with the commuting time of the victim $(\alpha''(c_i) < 0)$, the three relevant situations[3] are presented in figure 1. In the first two cases, both $h(c_i)$ and $\alpha(c_i)w_i$ are concave, but only in the first one, when spending to avoid victimization increasing more quickly with commuting time than the loss with victimization, all more been equal, a longer commuting time tend to be associated to victimization. From the equation (3) and the inclination of the loss function $(\alpha'(c_i)w_i)$, the condition for this situation is that $p'(h_i) < F/[\alpha(c_i)w_i + F]^2$ in the intersection point. This corresponds to a limit for the increase in the probability of apprehension associated to an increase in the spending. In the third case, the relation $h(c_i)$ is convex and again longer commuting times tend to be associated to victimization. From the second derivate of $h(c_i)$, shown below, we note that it is a more difficult case to verify.

$$\frac{d^2h(c_i)}{dc_i^2} = \frac{Fw_i\{A\alpha''(c_i - (2Ap'(h_i) + Fp''(h_i))\alpha'(c_i^2 w_i\}}{[\alpha(c_i)w_i + F]^4 p'h(i)^3} \tag{4}$$

Where $A = [\alpha(c_i)w_i + F]^2 p'(h_i)$. Thus, for $(d^2h(c_i))/(dc_i^2) > 0$, we must have $p''(h_i)$ negative and large in absolute value. This condition is the same of the one obtained by Gaviria and Pagés (2002) for a positive relationship between wealth and victimization because the economic force here is the same: with $p(h_i)$ exhibiting sharp diminishing returns to scale, it is more difficult for individuals with longer commuting to afford to the costs of protection against the greater risk of victimization.

To sum up, the model indicates that the condition for individuals with longer commuting

[3]The other situations, independent of the commuting time, all citizens would be victims or none of them would be victim.

time to be victims of a propriety crime is that, given an increment in the individual commuting time, the rate of expansion of the spending to avoid victimization is higher than that of expected loss of the crime. Certainly, this condition is more probable to vigor in urban environments of low or inefficient public guardianship.

3 Empirical Strategy and Data

In this work we are interested in estimating the causal effect of commuting time on the probability of being victim of urban violence in Brazilian metropolitan for individuals that takes more than certain commuting time for working (effect on treated). For this, we use a unique Brazilian data set that has simultaneously individual information of both victimization of urban violence and commuting time for all Brazilian metropolitan regions that is the PNAD (Pesquisa Nacional por Amostra de Domicílio) household survey of the year 2009.

The PNAD is an annually household survey conducted by the Brazilian government and only the year of 2009 there was supplement information about victimization and violence. Unfortunately, individuals were not assigned randomly to time commuting time categories, so we have to base our estimative on non-experimental methods. The PNAD data set, however, has a very rich set of information about the individual's personal, familiar, labor market and commuting characteristics. This makes it possible to match individuals with different commuting times based on their propensity score associated to the commuting time and on other characteristics.

A first more traditional linear econometric specification for obtaining the effect of commuting time on the victimization chance would be the following one:

$$Y = \alpha + \beta C + X\gamma + \epsilon \tag{5}$$

Where Y is an outcome related to victimization, C is an indicator for a longer commuting time (a dummy which value = 1 for individual with a long commuting time and = 0 otherwise, X is a set of control variables that affect the chance of victimization, and ϵ is an error term. In this perspective, the estimative of β would correspond to the effect of a longer commuting time on the chance of victimization. The known problem with this kind of approach to non-experimental data is that it is not possible to guarantee that the error term is uncorrelated to the variable measuring the impact of commuting time on victimization (C), which can makes the OLS estimative of β inconsistent and biased (Angrist and Pischke, 2009)[4].

Nevertheless, as we have, on one hand, a rich set of variables that influences the commuting time of the individuals and, on the other hand, the precise determinants of victimization appear a much broader set, in order to obtain a casual estimative of commuting time on the chance of being victim of urban violence in Brazilian metropolitan regions, we decide to match individuals based on their propensity score associated to their categories of commuting time (Angrist and Pischke, 2009). Similarly to Angrist and Haid (2004) argument, given the rich set of variables used for estimating the propensity score associated to commuting time, the potential influence of omitted variables is reduced.

[4] For example, risk lover people, more subject to urban dangers situation, can also choice longer commuting time, a situation makes difficult to identify the effect of a longer commuting time on victimization.

Our identification strategy is based on the conditionally independence or uncounfoudedness (Rubin, 1974; Heckman and Robb Jr, 1985) assumption and the propensity score theorem (Rosenbaum and Rubin, 1983). If we denote by Y_i the observed result of individual i for our outcome variable, the probability of being victim of urban violence, and Y_i^1 and Y_i^0 the potentials results of, respectively, taking the treatment (taking more than certain time in commuting to work) or not respectively, we have:

$$Y_i = C_i Y_i^1 + (1 - C_i) Y_i^0 \tag{6}$$

The uncounfoudedness assumption implies that, conditioned on a set of individual's variables X_i , the potential results are independent of being assigned to treatment, i.e., $Y_i^1, Y_i^0 \perp C_i | X_i$, where $\perp$ means independence. As shown, for example, in Angrist and Pischke (2009), this allows to obtain the effect of the treatment (in our case, a longer commuting time) as the difference in means of the outcome variable (in our case, the probability of being victim of urban violence) by status at each at each value of X_i.

Angrist (1998) proposed using a matching estimator when the X_i is discrete to obtain the sample correspondent to this difference in means of the outcome variable. Here, we use the Propensity Score Theorem of Rosenbaum and Rubin (1985) to obtain the effect of treatment on treated individuals. Specifically, we use the fact that $Y_i^1, Y_i^0 \perp C_i | X_i$ implies $Y_i^1, Y_i^0 \perp C_i | p(X_i)$, where $p(X_i)$ correspond to the probability of being treated or the propensity score (in our case, taking more than certain time for commuting from home to work location). In other words, conditioned on the propensity score, the potential results are independent of being assigned to the treatment. Using this theorem and the uncounfoudedness assumption, it is possible to obtain the effect of a longer commuting time on the probability of being victim of urban violence in Brazilian metropolitan regions of treated as (see Angrist and Prischke, 2009):

$$E(Y_i^1 - Y_i^0) = E\{E[Y_i | p(X_i), C_i = 1] - E[Y_i | p(X_i), C_i = 0]\} \tag{7}$$

In order to obtain the sample correspondence of equation (7), we estimate $p(X_i)$ using a logit model and use two ways of matching the treated with the controls, the nearest neighbor (one treated with one control) based on the estimative of propensity score and the kernel estimation for weighting controls according to propensity scores (one treated with weighted controls).

Apart from a large set of personal (age, gender, race, education), familiar (income, familiar structure, civil status, car owner) and labor market (economic activity sector, type of occupation) characteristics of the individuals living in Brazilian metropolitan regions, our data base presents information about individual victimization and the commuting time from home to work. For the victimization information, we have the if the individual was victim of robbery, theft and of physical aggression between September 27 of 2008 and September 26 of 2009. Then it is possible to work with an outcome variable associate to urban violence that represent the mean of the probability of being victim of urban violence for each one of these occurrences. Because it less suitable to information error, our emphasis in this work is on the victimization by robbery, but we also present some results for theft occurrence. As physical aggression can also be motivated by none economics factors, we do not consider this kind of urban violence.

As for the variable that represent the treatment, here a larger commuting time, we observe that the PNAD data set presents commuting time of the individuals organized in four categories, up to 30 minutes, more than 30 minutes and up to 1 hour, more than 1 hour and up to 2 hours, and more than 2 hours. From this information and because the average of commuting time of Brazilian metropolitan regions was 34.6 minutes in 2009 (closer to higher limit of the first category), we built a treatment indicator that assumes value equal to 1 if the individual takes more than 1 hour from his residence to his work location and equal to 0 if this commuting time is until 1 hour. Besides allowing meaningful distinction between individuals commuting time, note that this choice is also justified by theoretical reasons; specifically, under a urban environment of low public guardianship, it increases the probability of treated individual being in the situation when the additional spending to avoid being victim of crime is very high.

Our sample includes individuals of all ten official Brazilian Metropolitan Regions[5]. After considering only individuals with ten years old or more that have to commute for working, we have 52,296 observations for the year 2009. For each of these observations, we have an extensive set of variables that includes the potential determinants of victimization and of commuting time, including individual characteristics potentially associated to different degree of fragility and attractiveness, variables associated to location of the household in the metropolitan region (which includes both family characteristics and the degree of access of some infrastructure services) and variables associated to regular activities (Lemeiux and Felson, 2012; Messer et al. 2007; Beato, et al. 2004). The set of conditionings of commuting time also includes individual characteristics, civil status, family and household characteristics and employment characteristics (Fujita, 1989; Silveira Neto et al. 2014).

4 Results

From now on we will focus on display and analyse the main results, using mainly theoretical predictions obtained from the model previously developed. Our main prediction is that, in a urban environment of low or ineffective guardianship like the ones of Brazilian Metropolitan Regions, longer commuting is associated with a greater likelihood of victimization by urban violence, robbery been the focus.

Initially a brief description of the variables used as covariates, as well as the characteristics of the sampled individual's commuting are made. Followed by presentation of the preliminary results for the ols and logit specification, which however, may present biased since the assignment of individuals between treatment groups is not random. Witch justifies the use of estimation via propensity score matching. Finally the results of the propensity score matching estimates are presented. These results include difference sets of estimative by gender. We also present some checks for robustness using other kinds of matching and subsamples.

4.1 Commuting time and victimization in Brazilian Metropolitan Regions

In Table (1), we present the distribution of victims and non-victims of robbery and of theft across the commuting time categories for our sample of individuals of the Brazilian Metropolitan Regions. According to the numbers, 8.9% the individuals were victims of robbery and around 4.9% of them were victims of theft. The numbers of table 1 also indicate that for the victims of robbery

[5] Belém, Fortaleza, Recife, Salvador, Belo Horizonte, Rio de Janeiro, São Paulo, Curitiba, Porto Alegre e Brasília.

the proportions of individuals in the categories of shorter commuting time are lower than for non-victims. More specifically, while for the victims of this kind of violence the percentage of the individuals with more than one hour of commuting time is 15.9%, for non-victims this percentage is around 13.9%. These numbers are consistent with our expectations about the relationship between commuting time and chance of victimization by robbery. Note, however, that the numbers presented in table 1 do not show immediately the same kind of relationship when the crime is theft.

Table 1: Number of Victims by Commuting Time

Commuting	Robbery				Theft			
	NO	%	YES	%	NO	%	YES	%
<30 minutes	26354	0.543	2533	0.528	27445	0.541	1442	0.555
$\geq$ 30 minutes < 1 hour	15410	0.318	1497	0.312	16114	0.318	793	0.305
$\geq$ 1hour < 2 hours	5874	0.121	678	0.141	6244	0.123	308	0.119
$\geq$ 2 hours	871	0.018	86	0.018	904	0.018	53	0.020
Observations	48509	0.910	4794	0.090	50707	0.951	2596	0.049

[1] Source: Author's calculation based on PNAD 2009 microdata.

In Table (2), we present descriptive statistics of the set of variable we use to obtain our estimative; the variables are presented both for individual with and without long commuting time (more than one hour of commuting), respectively, treated and controls. The variables are organized in four groups and represent, respectively, individual characteristics associated to fragility or attractiveness of potential victims (individual), labor market variables associated to the location and kind of jobs (labor market), household and family variables associated to family structure and residence location (household and family) and the Metropolitan Regions location. As expected from a non-random sample of treated and controls, we first note that the characteristics are not well balanced between the two groups, as can be noted by the statistically significant differences between the two groups.

More specifically, for example, the proportion of white individuals is lower and individuals tend to be younger for the long commuting time group than for the group of control. We also note that both set of variables associated to labor market location and the kind of job and to household characteristics present significant differences between the two groups. Specifically, the proportions of informal employed and self-employed individuals, for example, are clearly higher for the group of control than for the group of individuals with long commuting time and the same happens for the proportion of owners of car. Finally, as expected, the proportion of individual living in the MR of São Paulo and Rio de Janeiro, the two biggest MRs of Brazil, are higher for the treated individuals than for individuals of the control group, the opposite happens to the eight other regions.

The two last lines of Table (2) just confirm the evidence of table (1): among the individuals with long commuting time (treated), the proportion of victims of robbery are higher than for the individuals of the control group, but the same cannot be stated for the crime of theft. But, as the distribution of the individuals between the two groups was not random, neither are the variables balanced between them, no casual inference is possible at this stage.

Our dataset allow us to identify the location of the crime occurrence and this is presented in Table (3). Observing the mentioned Table (3) we can see that the minority of the robberies (6.4%)

Table 2: Descriptive Statistics

	Treated		Control		
Variables	Mean	SD	Mean	SD	Diff
gender	0.569	0.495	0.568	0.495	-0.001
race	0.434	0.496	0.479	0.500	0.045***
age (years)	36.453	11.801	36.743	12.353	0.289**
age squared	1468.11	932.800	1502.617	990.133	34.509**
single	0.445	0.497	0.442	0.497	-0.002
highschool	0.446	0.497	0.408	0.491	-0.038***
college	0.110	0.313	0.153	0.360	0.043***
Household Income (R$)	774.11	956.66	1016.90	1617.60	242.79***
			Work Sector		
Industry	0.134	0.340	0.137	0.344	0.004
Construction	0.105	0.306	0.082	0.275	-0.023***
Commerce	0.159	0.366	0.209	0.407	0.050***
Public Administration	0.058	0.234	0.066	0.249	0.009***
Informal	0.188	0.391	0.219	0.414	0.031***
Self Implyed	0.076	0.266	0.140	0.347	0.064***
			Household Characteristics		
Dependency	0.031	0.146	0.032	0.156	0.001
car	0.383	0.486	0.449	0.497	0.066***
family size	3.490	1.397	3.402	1.366	-0.089***
Sanitation	0.682	0.466	0.622	0.485	-0.060***
Garbage	0.882	0.323	0.884	0.320	0.003
Piped Water	0.927	0.260	0.921	0.270	-0.006**
			Metropolitan Regions		
Belem	0.043	0.202	0.067	0.249	0.024***
Fortaleza	0.084	0.277	0.105	0.306	0.021***
Recife	0.077	0.267	0.086	0.280	0.008***
Salvador	0.100	0.300	0.117	0.322	0.017***
Belho Horizonte	0.092	0.289	0.097	0.296	0.005*
Rio de Janeiro	0.200	0.400	0.112	0.316	-0.088***
São Paulo	0.100	0.300	0.131	0.337	0.015***
Curitiba	0.049	0.215	0.064	0.244	0.0312***
Porto Alegre	0.054	0.225	0.141	0.348	0.087***
Distrito Federal	0.068	0.251	0.083	0.275	0.015***

Signifance Levels: * 10%, ** 5% and *** 1%. Source: Author's calculation based on PNAD 2009 microdata.

happened in residencies, that non less than 75% of them occurred in public ways, and around 9.2% occurred during public transportation. Given that the commuting time for working is commonly the most regular activities individuals do using public ways or public transportation, these data appear consistent with a positive relationship between commuting time and the chance of being victim of robbery. Nevertheless, the information for the crime of theft is evenly split among the categories of locations. In particular, we note that more the 30% of the occurrences of theft were at some residence. This is also consistent with the apparent less important role of commuting time for explaining victimization in Brazilian Metropolitan Regions we have note before.

Table 3: Distribution of Victimization by place of occurence

Where	Robbery	%	Theft	%
Own house? Or a third person house?	304	6.34	834	32.13
Commercial Estabishment	376	7.84	379	14.60
Public Way	3600	75.09	976	37.60
Teaching Establishment	15	0.31	46	1.77
Public Transportation	442	9.22	217	8.36
Gynnasion or Sports Stadium	6	0.13	10	0.39
Other	51	1.06	134	5.16
Total	4794	100.0	2,596	100.00

[1] Source: Author's calculation based on PNAD 2009 microdata.

4.2 Traditional measuring: OLS and Logit specifications

Initially, we provide measures of the association between long commuting time and the probability of victimization using more traditional specifications represented by a linear probability model (LPM) and a logit model (logit). The results are shown in Table (4) must be seen initially as just associations between the two variables. For the two kinds of urban violence (robbery and theft), we present results of the association between long commuting time (commuting) and the probability of being victim without (columns (1), (3), (5) and (7)) and with a set of controls variables (columns (2), (4), (6) and (8)). These controls variables include individuals characteristics potentially associated to attractiveness and fragility, household and residential characteristics, characteristics of the employment, and the individuals' Metropolitan Region.

From the numbers of Table (4), we note that effect of the long commute on the chance of victimization for robbery is positive and significant in all specifications (columns (1) to (4)). In other words, the positive association between long commute on the chance of victimization for robbery does not depend on the particular econometric model, neither of the controls. The same is not true in the case of theft; only after controlling for the influence of covariates that potentially affect the victimization chance we found a positive association between long commute on the chance of victimization for theft and this association is only statically significant at 10%.

As regarding the control variables, we not that at least one variable of each group (individual, household, employment, and location) is relevant to explain the variation in the chances of victimization among the individuals, with appears consistent with the idea that the chances of victimization are influenced by factors of different dimension of the social life.(Lemeiux abd Felson, 2012; Messer et al. 2007; Beato, et al. 2004).

Table 4: Effect of Long Commuting on Robbery and Theft Victimization

	Dependent Variable:							
	Robbery				Theft			
	LPM		Logit		LPM		Logit	
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commuting	0.014 ***	0.021 ***	0.160 ***	0.259 ***	-0.001	0.005 *	-0.016	0.107 *
	(0.004)	(0.004)	(0.042)	(0.044)	(0.003)	(0.003)	(0.058)	(0.060)
gender		0.012 ***		0.155 ***		0.008 ***		0.165 ***
		(0.003)		(0.033)		(0.002)		(0.044)
race		0.003		0.044		0.001		0.014 *
		(0.003)		(0.036)		(0.002)		(0.047)
age		-0.002 ***		-0.025 ***		0.000		0.009
		(0.001)		(0.007)		(0.000)		(0.010)
age2̂		0.000* *		0.000 **		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
single		-0.015 ***		-0.203 ***		-0.007 ***		-0.153 ***
		(0.003)		(0.035)		(0.002)		(0.045)
highschool		0.011 ***		0.144 ***		0.002		0.041
		(0.003)		(0.037)		(0.002)		(0.049)
college		0.011 **		0.143 **		0.008 *		0.173 **
		(0.005)		(0.060)		(0.004)		(0.071)
Household Income		0.000		0.000		0.000 *		0.000 *
		(0.000)		(0.000)		(0.000)		(0.000)
Dependency		-0.021 ***		-0.277 ***		0.010 *		0.191 *
		(0.007)		(0.107)		(0.006)		(0.111)
car		0.002		0.028		0.009 **		0.193 ***
		(0.003)		(0.038)		(0.002)		(0.048)
family size		-0.002 *		-0.023 *		-0.003 ***		-0.057 ***
		(0.001)		(0.012)		(0.001)		(0.017)
Industry		-0.024 ***		-0.321 ***		-0.007 **		-0.151 **
		(0.004)		(0.053)		(0.003)		(0.066)
Construction		-0.025 ***		-0.329 ***		-0.007 *		-0.146 *
		(0.005)		(0.066)		(0.004)		(0.084)
Commerce		0.005		0.056		0.000		0.001
		(0.004)		(0.040)		(0.003)		(0.054)
Public Administration		-0.028 ***		-0.384 ***		-0.006		-0.109
		(0.005)		(0.074)		(0.004)		(0.087)
Informal		-0.005		-0.062		-0.001		-0.023
		(0.003)		(0.041)		(0.002)		(0.055)
Self Implyed		0.008 *		0.095 *		0.008 ***		0.171 ***
		(0.004)		(0.049)		(0.003)		(0.063)
Sanitation		0.008 **		0.099 **		0.001		0.027
		(0.003)		(0.041)		(0.002)		(0.053)
Garbage		0.003		0.038		0.001		0.013
		(0.004)		(0.050)		(0.003)		(0.068)
Piped Water		0.003		0.040		-0.004		-0.083
		(0.005)		(0.058)		(0.004)		(0.081)
Intercept	0.088***	0.108 ***	-2.338 ***	-2.168 ***	0.049 ***	0.034 ***	-2.970***	-3.283 ***
	(0.001)	(0.014)	(0.016)	(0.172)	(0.001)	(0.011)	(0.022)	(0.235)
Metropolitan Dummy	NO	YES	NO	YES	NO	YES	NO	YES
Observations	53303	52296	53303	52296	53303	52296	53303	52296
R2		0.024				0.004		
F Statistic	13.56	32.383			0.07	7.108		

Signifance Levels: * 10%, ** 5% and *** 1%.

4.3 Propensity Score Matching Results

As the individuals were not distributed randomly between the two groups with different commuting times, neither the set of controls variables are balanced between these two groups, the individuals with short commuting we used to obtain the estimative presented at Table (4) are not an acceptable set of counterfactuals to the ones with long commuting time. In order to minimize this problem, we implement matching based on the propensity score estimative and generate new estimative for the effect of long commuting time on the probability of being victim of robbery or theft in Brazilian Metropolitan Regions. Our expectation is that, by balancing the set variables the determines the commuting time of the individuals between the two groups, we can eliminate or at least minimize the influence of potential omitted determinants of victimization that are correlated with commuting time of the individuals.

For the propensity score estimative, based on both traditional Urban Economics Theory and recent empirical studies, we use a the set of variables presented at table 3, which includes individual characteristics, residential characteristics, variables associated to family structure, variables for sectors of activities and the kind of job, and the identification of the MR (Fujita, 1989; Silveira Neto et al. 2014; McKenzie and Rapino, 2011; Crane, 2007)[6] . At the Table (5), we present the set of variables we used to obtain the propensity score estimative. The set of variables are presented both for treated (long commuting) and control groups and both for the sample of unmatched and matched individuals, when the matching are made using the nearest-neighbor criteria.

As can be noted from the t-statistic also presented at the Table (5) for the test of difference of values between treated (long commuters) and controls, although the differences are statistically significant for the unmatched sample, after comparing the long commuters with their respective nearest-neighbor based on propensity score estimative, none difference appears statistically significant at 1%. This means that the set of characteristics is well balanced between long commuters and controls, a condition necessary for measuring the impact of commuting on the probability of being victim of violence. Note that, for the most of the cases, we also obtained significant bias reduction.

The results of the propensity score matching estimations are presented in Table (6). In Panel A we have the results for robbery using both the nearest neighbor approach to the matching and the kernel weighting for matching, in panel B we present the results for theft using these two criteria for matching. Independently of the propensity score based matching criteria, our results indicates that long commuters (treated) have a higher probability of being victim of robbery than individual without long commuting time in Brazilian Metropolitan Regions. Specifically, according to nearest-neighbor estimative, long commuters have a 2.1% increase in the probability of being victim of robbery as compared to individuals without long commuters, a difference that correspond to 1.7% in the case of the kernel matching estimative.

As for the crime of theft, our estimative do not indicate any positive effect of a longer commuting on the probability of being victim in Brazilian Metropolitan Regions, independently of the propensity score based matching criteria of proximity we use. This result, at least in part, is probably explained by the local of occurrence of many thefts; differently from robbery, a significant parcel of thefts in Brazilian Metropolitan Region tends to occurs at home (see Table 4). In addition, this kind of crime tends to be much more dependent of specific circumstances.

[6]For space reasons, we do not present the estimative for the logit model of the determinants of commuting time but they are availed upon request.

Table 5: Comparisons between Long Commuters (Treated) and Short Commuters (Control) in the Original (Unmatched)
and the (Nearest-neighbor) Matched sample.

Variable	Unmatched Sample				Matched Sample				
	Treated	Control	t-test	% bias	Treated	Control	t-test	% bias	% bias Reduction
gender	0.5711	0.56963	0.24	0.3	0.57092	0.5716	-0.08	-0.1	53.8
race	0.43394	0.47892	-7.16	-9.0	0.43411	0.44174	-0.93	-1.5	83.1
age	36.466	36.754	-1.87	-2.4	36.464	36.652	-1.6	-0.97	34.6
age squared	1468.3	1502.9	-2.81	-3.6	1468.1	1481	-1.3	-0.84	62.7
single	0.44659	0.4441	0.40	0.5	0.44677	0.4401	1.3	0.81	-167.8
highschool	0.44564	0.40775	6.12	7.7	0.44582	0.43983	1.2	0.73	84.2
college	0.10913	0.15156	-9.57	-12.6	0.10918	0.11612	-2.1	-1.33	83.6
Household Income	774.11	1016.9	-12.51	-18.3	774.29	796.71	-1.41	-1.7	90.8
Dependency	0.03072	0.03186	-0.59	-0.8	.03073	0.03383	-2.1	-172.7	-1.21
car	0.38005	0.44704	-10.74	-13.6	0.38021	0.37993	0.03	0.1	99.6
family size	3.4799	3.393	5.05	6.3	3.4794	3.4937	-0.62	-1.0	83.5
					Working Sector				
Industry	0.13376	0.1381	-1.00	-1.3	0.13381	0.1394	-0.98	-1.6	-28.7
Construction	.10614	.08263	6.67	8.0	0.10577	0.1121	-2.2	-1.24	72.8
Commerce	0.15839	0.20931	-10.09	-13.2	0.15845	0.15981	-0.23	-0.4	97.3
Public Administration	.05769	.06648	-2.83	-3.6	0.05772	0.05459	0.82	1.3	64.4
Informal	0.18805	0.21852	-5.90	-7.6	0.18813	0.18677	0.3	0.21	95.5
Self Imployed	0.07715	0.1407	-14.96	-20.5	0.07718	0.07895	-0.40	-0.6	97.2
					Infraestructure				
Sanitation	0.67955	0.622	9.48	12.1	0.67983	0.67533	0.9	0.58	92.2
Garbage	0.8808	0.88395	-0.78	-1.0	0.88116	0.88116	0.00	0.0	100.0
Piped Water	0.92598	0.92091	1.50	1.9	0.92608	0.92704	-0.22	-0.4	81.2
					Metropolitan Regions				
Belem	0.04273	0.0657	-7.55	-10.2	0.04274	0.04097	0.54	0.8	92.3
Fortaleza	0.08545	0.10588	-5.34	-6.9	0.08549	0.08835	-0.61	-1.0	86.0
Recife	0.07851	0.08561	-2.03	-2.6	0.07855	0.07855	-0.00	0.0	100.0
Salvador	0.10137	0.11827	-4.20	-5.4	0.10142	0.09257	1.81	2.8	47.6
Belho Horizonte	.09321	0.09743	-1.13	-1.4	0.09325	0.09012	0.66	1.1	25.7
Rio de Janeiro	0.19948	0.1114	21.35	24.5	0.19943	0.20161	-0.33	-0.6	97.5
Curitiba	0.04939	0.06425	.04941	-6.4	0.04941	0.05391	-1.23	-1.9	69.8
Porto Alegre	0.05348	0.14083	-20.83	-29.8	0.0535	0.05636	-0.76	-1.0	96.7
Distrito Federal	0.06817	0.08221	-4.11	-5.3	0.0682	0.06425	0.96	1.5	71.9
Observations	7,509	45,794			7,509				

Note: The standardised bias is the difference of the sample means in the treated and non-treated (full or matched) sub-samples as a percentage of the square root of the average of the sample variances in the treated and non-treated groups, see Rosenbaum and Rubin (1985). Signifance Levels: * 10%, ** 5% and *** 1%.

Table 6: Propensity Score Matching Results for Robbery and Theft

	Sample	Treated	Control	Diff	St Err.	Bootstrap St Err,
Panel A:	Robbery					
Nearest Neig. Matching	Unmatched	0.1021	0.0878	0.0142***	0.0036	
	Matched	0.1021	0.0805	0.0216***	0.0052	0.0062
Kernel Matching	Unmatched	0.1021	0.0878	0.0142***	0.0027	
	Matched	0.1021	0.0847	0.0174***	0.0038	0.0048
Panel B:	Theft					
Nearest Neig. Matching	Unmatched	0.0486	0.0488	-0.0002	0.0036	
	Matched	0.0486	0.0440	0.0046	0.0038	0.0031
Kernel Matching	Unmatched	0.0486	0.0488	-0.0002	0.0027	
	Matched	0.0486	0.0457	0.0029	0.0027	0.0028

[1] Robust standard errors are presented in parentheses; bootstrap standard erros where calculated using 200 replications for nearest neighbor matching and 50 replications for kernel matching,
[2] Signifance Levels: * 10%, ** 5% and *** 1%.

The crime literature as gives great focus on gender differences, especially in the case for public exposure, a common feature of the routine activity approach (Cohen e Felson, 1979). Given that the female gender can be considered more vulnerable under the perspective of potential offenders, we also performed estimation separated by gender. The results are presented in Table (7), both for more traditional econometric specifications (LPM and logit) and for two criteria of proximity based on propensity score matching.

As we can see, for the crime of robbery, independently of the method of estimation, we obtained positive and statistically significant estimative for the impact of a long commuting time on the probability of being victim. In all cases, all estimative indicates a higher effect of a longer commuting on probability of being a victim of robbery for women than for men; for example, for the matching based on the kernel weighing, the estimated impacts of a longer commuting are 2.2% and 1.5% increases in the probability of being victim of robbery, respectively, for women and men. For the case of theft, however, we found only a weak, but non-robust, evidence for the impact of a long commuting time on the probability of being victim when using kernel weighing for the propensity score.

4.4 Robustness Checks

So far, we successively found a positive statistical relation between commuting time and urban robbery victimization in Brazilian Metropolitan Regions. In this section, we test the robustness of this result by generating three additional sets of estimative. First, we use traditional LPM and logit specifications for the sample of matched individuals; second, following Abadie and Imbens (2002), instead of using only the propensity scores, we generate estimative by matching individuals based on the set of variables that are potentially associated to commuting time; finally, we gener-

Table 7: Effect of Long Commuting: Gender Differences

	Panel A: Men		Panel B: Women	
Estimation	Robbery (1)	Theft (2)	Robbery (1)	Theft (2)
LPM	0.019***	0 .00	0.025***	0.011**
	(0.005)	(0.004)	(0.006)	(0.004)
Logit	0.231***	0.00	0.299***	0.238***
	(0.058)	(0.004)	(0.066)	(0.09)
PS Nearest Neig. Matching	0.022***	0.004	0.025***	0.007
	(0.007)	(0.005)	(0.008)	(0.006)
	[0.008]	[0.006]	[0.009]	[0.006]
PS Kernel Matching	0.015***	0.004	0.022***	0.009***
	(0.005)	(0.005)	(0.006)	(0.004)
	[0.005]	[0.006]	[0.006]	[0.004]

[1] Note: On the linear probability model and logit estimates we use all controls use in the estimates of Table (4)

[2] Robust standard errors are presented in parentheses; bootstrap standard erros where calculated using 200 replications for nearest neighbor matching and 50 replications for kernel matching, they are presented in brackets.

[3] Signifance Levels: * 10%, ** 5% and *** 1%.

ate estimative using a restrict the sample that includes only individuals living in residence with a complete set of infrastructure house.

The first robustness check, we followed the suggestion of Crump et al. (2009) and used the sample obtained by matching each long commuter on a nearest-neighbor based on propensity score estimative. The idea is that, using only observations of treated and controls with a common support, we can eliminate the influence of observations without overlap in the covariates' distributions between these two groups. The new estimative of the impact of a long commuting on the probability of being of victim of robbery and of theft are presented at the first two lines of Table (8). Apart from a little reduction for the effect of a long commuting time on the probability of being victim of robbery, the results both for victimization by robbery and by theft are basically the same of the ones presented at Table (6) before, namely, a positive and statically significance impact for robbery and none effect for theft.

Our second robustness checks applied the bias-corrected matching estimator proposed by Abadie and Imbens (2002). Instead of matching only on propensity score, this estimator match the observations based on all the set of variables presented on Table (2)[7]. The estimative of the impact of a long commuting on the probability of victimization by robbery and by theft obtained using this

[7]We use the suggestion of Abadie et al. (2004) and used more than one nearest-neighbors (in our case, three) for matching each individual with a long commuting time. The reason for a bias correction arises because of the potential difference between the two groups related to the variables used for matching and it is implemented using predicted terms obtained though separated initial regressions of the outcome variable on the set of variables used for matching (Abadie and Imbens, 2002; Abadie et al., 2004).

estimator are presented in third line of Table (8). As can be noted, the estimative are quite similar to those obtained using the propensity score matching and the nearest-neighbor proximity criteria (Table (6)), specifically, a long commuting time implies an increase of 2.6% on the probability of being victim of robbery and none effect on the probability of of being victim of theft.

Finally, we applied propensity score matching using a sample of individual whose residences present a complete set of infrastructure services: access to regular services of sanitation, to piped water and to regular garbage collection. The idea is to verify if our results just reflect more violent poorer neighborhoods located in the fringes of Brazilian Metropolitan Regions with less public services, where individuals also present longer commuting times. The results are presented in the Table (8), an the effect remains unchanged and indicate that this potential source of bias cannot explain our main previous results. More specifically, even after eliminates the most important differences related to household infrastructure, which means discard the poorest neighborhoods, for the propensity score matching based on the nearest-neighbor, we estimate that a longer commuting time implies an increase of 1.8% on the probability of being victim of robbery in Brazilian Metropolitan Regions. The results of the checks are presented in Table (8), as the effect show robustness.

Table 8: Robustness Check

Outcome:	Robbery	Theft
Estimation	(1)	(2)
LPM	0.018***	0.001
	(0.005)	(0.004)
Logit	0.224***	0.033
	(0.058)	(0.077)
Bias Ajusted Variable Matching	0.026***	0.005
	(0.005)	(0.004)
PS Nearest Neigbor Matching	0.018**	0.007
	(0.006)	(0.005)
	[0.007]	[0.005]
PS Kernel Matching	0.012**	0.001
	(0.007)	(0.005)
	[0.005]	[0.005]

[1] Note: On the linear probability model and logit estimates we use a restricted subsample of individuals with a complete set of household infraestructure (sanitation, garbage pickup and piped water), and all controls use in the estimates of Table (4)
[2] For the bias ajusted variable matching the coeficient corresponde to the sample average treatment effect.
[3] Robust standard errors are presented in parentheses; bootstrap standard erros where calculated using 200 replications for nearest neighbor matching and 50 replications for kernel matching, they are presented in brackets.
[4] Signifance Levels: * 10%, ** 5% and *** 1%.

4 Simulation-based sensitivity analysis

Even though the matching quality and robustness checks results displayed above endorse the validity of our propensity score matching estimates, these results relies on the conditional independence assumption (CIA). As this identifying assumption is non-testable by its nature, one may still question the plausibility of this assumption in our case and argue that ultimately our results are being affected by an omitted variable strongly correlated with commuting duration.

With the purpose of remove this suspicion, we apply the simulation-based sensitivity analysis proposed by Ichino et al. (2008) as an additional resource to assess the robustness of our estimates. This analysis aims at assessing the bias of our estimates when the CIA is assumed to fail in some specific ways. A failure in the CIA is equivalent to say that the assignment to treatment is not unconfounded given the set of observable variables X, i. e., $Pr(C = 1|Y_0, Y_1, X) \neq Pr(C = 1|X)$. Although, adding the assumption that the CIA holds given X and an unobserved binary covariate U. If we could observe U the adapted CIA would be as follow, $Pr(C = 1|Y_0, Y_0, X, U) = Pr(C = 1|X, U)$.

Even though U is a unobservable confounding factor, Ichino et al. (2008) proposes a characterization of it's distribution using by specifying the following parameters. $p_{ij} \equiv Pr(U = 1|C = i, Y = j, X) = Pr(C = 1|C = i, Y = j); i, j \in \{0, 1\}$, Which define the probability that $U = 1$ in each of the four groups defined by the treament status (C) and the outcome value (Y)[8]. The parameters p_{ij} can be chosen to make the distribution of U similar to the empirical distribution of observable binary covariates, in this case, the simulation exercise reveals the extent to which matching estimates are robust to deviations from the CIA induced by the impossibility of observing factors similar to the ones used to calibrate the distribution of U.

Ichino et al. (2008) points out that despite it's simplicity, this sensitivity analysis has several advantages. First, the hypothesized associations of U with Y and C are stated in terms of proportions characterizing the distribution of $U|C, Y, X$. This avoids a possibly incorrect parametric specification of the distribution of $U|C, Y, X$, which is the strategy adopted by competing types of sensitivity analysis like

Second, the parameters p_{ij} can be chosen to make the distribution of U similar to the empirical distribution of observable binary covariates. In this case, the simulation exercise reveals the extent to which matching estimates are robust to deviations from the CIA induced by the impossibility of observing factors similar to the ones used to calibrate the distribution of U.[9] Third, one can search for the existence of a set of parameters p_{ij}. such that if U were observed the estimated ATT would be driven to zero[10], and then assess the plausibility of this configuration of parameters.

About the interpretation of the sensitivity analysis, one might be tempted to interpret the

[8]Given these parameters, the next step is to predict a value of the confounding factor for each treated and control subject and re-estimate the ATT including the simulated U in the set of matching variables, treated as any other covariate. Employing a given set of values of the sensitivity parameters, the matching estimation is repeted m times to obtain an estimate of the ATT, which is an average of the ATTs over the distribution of the simulated U. Thus, for any given configuration of the parameters p_{ij}, we can retrieve a point estimate of the ATT which is robust to the specific failure of the CIA implied by that configuration.

[9]As enphasise by Ichino et al. (2008) this is a different exercise from the simple removal of an observed variable from the matching set X, since in our simulations we are still controlling for all the relevant covariates observed by the econometrician.

[10]Know as "killer confounder".

difference $d = p01 - p00$ as a measure of the effect of U on the untreated outcome, and the difference $s = p1. - p0.$ as a measure of the effect of U on treatment assignment. But these effects must be evaluated after conditioning on X because even if the distribution of U given X and Y does not vary with X, there will be in the

To sidestep this shortcoming, Ichino et al. (2008) implement the sensitivity analysis by measuring how the different configurations of p_{ij} chosen to simulate U translate into associations of U with Y_0 and C (conditioning on X). More precisely, by estimating a logit model of $Pr(Y = 1|C = 0, U, X)$ in every iteration, the effect of U on the relative probability to have a positive outcome in case of no treatment (the observed "outcome effect" of the simulated U) as the average estimated odds ratio of the variable U, denoted Γ. Similarly, by estimating the logit model of $Pr(C = 1|U, X)$, the average odds ratio of U would measure the effect of U on the relative probability to be assigned to the treatment $T = 1$ (the observed "selection effect" of U), denoted by Λ.

Following this reasoning, we proceeded the sensibility analysis calibrating U to first mimic a neutral confounder in the sense that set of the effect on the untreated outcome is zero ($p01-p00 = 0$) and the effect on the selection into treatment is also zero ($p1. - p0. = 0$). Then we mimic other observed covariates and finnaly, consider a parameter specifications would ultimatly driven the effect of long commuting in the chance os being victim to zero, and assess it's plausability.The Results as show in Table (9). As can be seen in Table a unobserve confounder U like any of the observable covariates would not sufice to reduce the effect to zero, on the contrary, the effect still remains virtually unaltered, wich is plausible given the small outcome and treatment effect of these unconfounding factors. The necessary confounding factor U to reduce the effect of commuting in the chance of being victim would need a $\Gamma = 2.3$ and a $\Lambda = 6.9$. More precisely, U must increase the relative probability of having Y above the mean by a factor greater than 2.3, and the relative probability of being treated by almost 7. The presence among unobservable factors of a confounder with similar characteristics can be considered implausible, given that important covariates for crime victimization such as gender or race had such a small effect for a mimic U. These simulation exercises support the robustness of the matching estimate.

5 Concluding Remarks

Because their associated impact on urban life quality, urban violence and long commuting time to work location are certainly among the biggest urban problems of Brazilian Metropolitan Regions. The set of evidence obtained in this research indicates that these problems are not dissociated; specifically, using a unique household survey that have collected both information about commuting time and victimization (the supplement of PNAD 2009), we obtain robust evidence that a long commuting time for individuals living in the Brazilian Metropolitan Regions increases the probability of these individuals being victims of robbery. This main result is consistent with both routine activities theory (Cohen and Nelson, 1979; Cohen et al., 1981) and the economic incentives approach to crime (Becker, 1968), once a longer commuting time increases the exposure of individuals to less security locations and implies higher expected gains for the potential criminal.

More specifically, obtained from using propensity score matching technics for creating counterfactuals for the treated group, our results show that individuals with more than one hour of commuting have an over all 2.1% increase in the probability of being victim of robbery, with no

Table 9: Sensitivity Analysis: Effect of Calibrated Confounders

	$Pr(U=1\|C=i,Y=j)$				Γ	Λ	ATT	SE
	p11	p10	p01	p00				
No confouder	.00	.00	.00	.00	-	-	0.022	0.005
Neutral Confouder	.50	.50	.50	.50	1.005	0.997	0.022	0.006
Confouder like								
Gender (male=1)	0.56	0.57	0.59	0.57	1.098	1.011	0.022	0.006
Race (white=1)	0.42	0.44	0.43	0.48	0.808	0.833	0.021	0.006
Single	0.40	0.45	0.37	0.45	0.713	1.008	0.022	0.006
Highschool	0.46	0.44	0.45	0.40	1.219	1.171	0.021	0.006
College	0.11	0.11	0.14	0.15	0.912	0.687	0.021	0.006
Own a Car	0.35	0.39	0.40	0.45	0.815	0.759	0.020	0.006
Sanitation	0.64	0.69	0.59	0.63	0.858	1.306	0.022	0.006
Garbage	0.88	0.88	0.87	0.89	0.845	0.978	0.022	0.006
Pipewater	0.92	0.93	0.90	0.92	0.766	1.091	0.022	0.006
“killer confounder”	0.80	0.80	0.55	0.35	2.285	6.904	-0.007	0.007

[1] Γ is the average estimated odds ratio of U in the logit model of $Pr(y=1|C=0;U;X)$; Λ is the average estimated odds ratio of U in the logit model of $Pr(C=1|U;X)$;“ATT” is the average of the simulated ATTs; “SE” is the standard error calculated as shown in Ichino et al., 2008.

robust impact on theft. We also found larger effect on the probability of robbery victimization for women than for men (respectively, 2.5% and 2.2% increases in the probability of being victim of robbery). The results are robust to different robustness checks, including estimative excluding the poorest neighborhoods located in the fringes of the Brazilian Metropolitan Regions where a longer commuting can potentially coexist with urban violence. Also, the performed sensitivity analysis incates that the presence of unobservable factors would not suffice to driven our results, therefore supporting the matching estimate.

There is a clear policy implication of our results. Without taking into account this identified effect of a long commuting time on the probability of victimization, the urban police makers of Brazilian Metropolitan Regions are underestimating the gains of welfare associated to a more effective transport system; our results indicate that, apart from the gains associated to the longer time available for working or leisure, in an social environment of weak guardianship, an increase of urban mobility implies direct gains of welfare associate to less exposure to more risk locations.

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