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URBAN MOBILITY: Relationship with insecurity and domestic violence

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Dedication

Dedicated to Amira y Malta.

Acknowledgments

- To Carlos Rodríguez and Rodrigo Troncoso for supervising this research
- To my boss, Eugenio Guzmán, for all the support
- To my Faculty mates
- To my CICS mates
- To my Family
- To myself

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1. Introduction

The development of Data Science and Computational Social Sciences have made it possible to characterize and model many phenomena and social dynamics from new sources of information and large volumes of data, such as digital traces and geolocated information [31].

Urban Mobility can be studied at two levels: macro and micro. At the macro level, most quantitative studies have used origin-destination surveys. At the micro level, mobility has been studied and characterized from digital traces. The use of mobile devices has made it possible to explore on a larger scale the mobility of people and their patterns in the city [18, 7, 2, 19, 35, 17], it being a source for studying human behavior and interactions between people [5] reducing the biases that self-reports of origin-destination surveys can generate, and provide an opportunity to study the behavior and mobility of people and their relationship with variables of social interest, to a scale that the macro level does not reach. From these devices, it has been observed that human trajectories show a high degree of temporal and spatial regularity [18]. However, differences in mobility patterns have also been observed when users differ by some factors such as gender [17].

In this thesis, this mobility measurement approach based on digital traces was used to explore how mobility is related to two social phenomena: insecurity and domestic violence against women. The female mobility patterns are different from males, and these social phenomena have the power to modify their behavior, restricting habits and possibly activities in their daily life [26, 9].

Individual factors play a significant role in determining the risk of victimization and shaping perceptions of safety, despite fear being prevalent in society [9]. Traditionally, women are more fearful (particularly in public spaces) than men about their personal safety [6, 30, 32, 9]. A specific element of perceived safety and changes in habits that female present compared to men is strongly linked to crime victimization, since in general, they are socially and physically more vulnerable to crime, since they tend to have less physical strength and less ability to defend themselves [37, 39]. The literature indicates that women's greater fear of crime, compared to men, can be explained to a large extent by the fear of being a victim of a sexual crime, this is the "shadow of sexual assault hypothesis" [13, 34, 23, 33].

There are other factors at the community, household and individual levels that determine the ability of women to make decisions about their mobility [12]. Socially, the control of female mobility is observed from two perspectives: by the woman's partner and by the woman herself. There are negative attitudes and controlling behaviors of the partner towards female mobility conditioned, for example, to the domestic responsibilities. This control over daily activities can range from mild to severe, potentially escalating to domestic violence if the woman chooses to not comply with the partner's expectations. [29, 12]. Under an "agency" approach, which emphasizes empowerment and financial autonomy, women can work towards achieving their life goals, such as freedom from domestic violence and greater mobility [29, 12]. This approach describes the phenomenon of violence against women and its causes in terms of social and psychological characteristics of the victim and the aggressor. Education and employment would be conditioning factors of violence against women [4, 24].

Education has been identified as a protective factor against domestic violence, as limited access to education increases the likelihood of experiencing violence [43, 15, 1, 41, 28]. Regarding employment, there is no consensus [21, 10, 41]. While women's access to employment can reduce the likelihood of experiencing domestic violence by providing independence and economic autonomy [16, 11, 3, 14]; this risk is dependent on their partner's employment status [3]. Female labor force participation can reduce the risk of domestic violence when the partner is also employed, but can increase the risk of violence when the partner is not employed [21].

Therefore, to the extent that personal security and victimization by domestic violence against women impact routines and lifestyles, this thesis proposes as a general hypothesis that at higher levels of insecurity and domestic violence, lower levels of mobility will be observed. Specifically, two studies were developed: "Gender gaps between urban mobility and insecurity" and "Mobility and domestic violence against women".

Four sources of information were used for the characterization and quantification of these phenomena:

1. Police geolocalized records from the Center for the Study and Analysis of Crime (CEAD) of the Ministry of the Interior, Chile. These records, available since 2012, correspond to Crimes of Greater Social Connotation, Domestic Violence, Breaking Weapons Law, Breaking Drug Law and Incivilities.

2. National Urban Survey of Citizen Security (ENUSC) of the National Institute of Statistics (INE), Chile, 2017. Its objective is to evaluate the perception of insecurity, the reaction to crime and the victimization of people and households.

3. The Census of Population and Housing of Chile, conducted in 2017, provides territorially disaggregated socioeconomic information to describe the population living in the country.

4. Anonymized records or Call Detailed Records (CDRs) of mobile phone of Telefónica Chile. These records, for the months of May, June and July of 2016, have information on gender, nationality, socioeconomic segment and the number of phone lines registered and associated with a specific phone number.

1.1 Gender gaps between urban mobility and insecurity

The main objective of this study is to evaluate the relationship between mobility and insecurity, with a focus on how it differs between genders, based on the hypothesis that when faced with a greater feeling of insecurity, lower levels of mobility are observed, and this relationship is stronger in women. Two measures of mobility were used, entropy and the number of trips [38, 17], constructed from digital traces of mobile devices. The perception of insecurity was obtained from the Chilean National Urban Survey of Citizen Security. An indicator of emotional, cognitive and evaluative insecurity [27] was constructed. The emotional dimension of insecurity was evaluated in different situations and places: buses, bus stops, collective taxis, subways, neighborhood squares and parks, neighborhood sports courts and streets. The study was conducted in Santiago, Chile.

The relationship between mobility and lack of safety was described using the Pearson correlation index. Causality and the gender gap were evaluated with linear regressions by Ordinary Least Squares (OLS) considering, in addition to insecurity as an independent variable, a dummy variable referring to gender, and its interaction with insecurity. A joint significance test was performed as evidence of a relationship between mobility and insecurity differentiated by gender [20, 8]. Bootstrapping was applied and Bayesian estimates were made to validate and provide robustness to the inference of the results.

A causal relationship is observed, which would imply that the mobility of people would decrease in the face of a greater perception of insecurity. This relationship, although it exists among men as well, is stronger in women as they tend to further reduce their mobility habits, particularly in places such as buses, bus stops, neighborhood squares, parks, neighborhood sports courts and on the street when they perceive the same level of insecurity.

It is concluded that gender by itself does not explain mobility. Although there is a gender gap in mobility, since women move less than men [17], this reduction is even greater in women if we control for the perception of insecurity.

1.2 Mobility and domestic violence against women

Female and male mobility patterns differ, with women visiting fewer places in their daily movements [36, 17]. According to the World Bank, this is because they spend more time on housework and childcare, so they tend to take fewer or shorter trips [40]. Negative attitudes of partners and control behaviors, due to the belief that they are responsible for household chores, could be determinants of female mobility [12].

Education has been identified as a protective factor against domestic violence, as limited access to education increases the likelihood of experiencing violence [43, 15, 1, 41, 28]. Regarding employment, there is no consensus [21, 10, 41]. While women's access to employment can reduce the likelihood of experiencing domestic violence by providing independence and economic autonomy [16, 11, 3, 14]; this risk is dependent on their partner's employment status [3]. Female labor force participation can reduce the risk of domestic violence when the partner is also employed, but can increase the risk of violence when the partner is not employed [21].

To the extent that women are victims of domestic violence, which impacts their routines and lifestyles, the hypothesis was proposed that higher levels of domestic violence lower levels of mobility. The present study is an exploratory analysis whose main objective was to evaluate the relationship between mobility and domestic violence against women. We define female mobility as entropy and the number of trips [38, 17], both measures constructed from digital traces of mobile devices. Domestic violence against women, defined as physical and psychological violence, was quantified from police records from the Center for Crime Studies and Analysis (Chile). The study was conducted in Santiago, Chile.

The relationship between mobility and domestic violence was described using the Pearson correlation index together with a multivariable regression by Ordinary Least Squares (OLS) considering, in addition to domestic violence, variables related to economic autonomy, such as female education and employment. To isolate the effect of education and employment on the relationship, a matching method was used. This method has the advantage of controlling for multiple factors, in our case, female education and employment. As domestic violence is not a dummy variable, a Generalized Propensity Score (GPS) was used to estimate causal effects for a continuous exposure variable [22, 25, 44, 42]. Bootstrapping was applied to our models to validate and provide robustness to the inference made.

Our results show a significant relationship between female mobility and domestic violence against women. This relationship is observed in physical violence and not in psychological violence. This would imply that female mobility would decrease in the face of a higher rate of physical domestic violence. Although female employment and education are related to their mobility, our analysis does not provide evidence to conclude that they explain it.

1.3 Policy Implications

The gender gap and mobility restrictions represent a greater cost for women in terms of time and well-being. When women leave their homes, they experience constant exposure to security risks, fear and stress during displacements, harming their emotional well-being. In areas with high levels of crime and violence, women prioritize safer travel options, which often means longer travel times. At the household level, inequality in the assignment of functions determines mobility and labor decisions [12]

A reduction in mobility affects the personal and professional development of women. If accessibility is defined as "the ease with which an individual can access opportunities within the space of the city" [12], mobility is reduced by victimization and insecurity, affecting female accessibility by restricting the area and the costs of their trips, social interaction, as well as their employment options [12].

The ability to move freely is an essential human right that facilitates participation of people in social and economic life. Given this, the design of public policies must consider all social phenomena that have the power to modify behavior and restrict the habits and activities in the daily life of people [26, 9]. These policies will be effective with a good design and implementation of social programs and projects that consider, as a result, an effect on the mobility of people. Social programs that seek to reduce gender violence must focus on both men and women. In men to eliminate or reduce controlling attitudes towards women, and in women to empower them and increase their autonomy. In social projects, the design of infrastructure would increase the perception of security and therefore female mobility. For example, in public transport, the existence of buses or subway cars exclusively for women, as well as bus stops with a gender perspective[1].

Public policies that address the crime problem will directly affect female perception of safety, changing their mobility patterns. However, the feeling of female safety is not only affected by their previous victimization or perception of crime, but also by the fear that incivilities generate in them. These disorders or faults that occur mainly in public space and that negatively affect its use by citizens must be considered in public policy. It is essential to recover public spaces for people and reject acts of vandalism or disorder that disturb social coexistence and therefore their mobility.

The main challenge facing public policy makers is to design comprehensive interventions to address the multiple aspects that affect female mobility. Therefore, the design and targeting of interventions that reduce or eliminate these phenomena (crime, insecurity, domestic violence) must consider and have as a priority factor, an effect on mobility differentiated by gender.

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2. Gender gaps in the perception of safety, urban mobility and the relationship between the two

In this study, we investigate the relationship between perceptions of insecurity and mobility, with a focus on gender differences. Using both self-reported perceptions of insecurity and digital mobile phone traces, we analyze the impact of insecurity on daily life activities and habits, specifically mobility. Our results reveal that insecurity has a significant impact on mobility for both men and women, however, the effect is more pronounced among women. Given that women generally report higher levels of insecurity, it is important for public policy to prioritize the recovery of public spaces where women may feel more insecure, such as bus stops, squares, neighborhood parks and sports courts, and the street.

2.1 Introduction

Crime and violence are social phenomena that have been studied for many years from different perspectives. The occurrence of a crime has psychological, perceptual and behavioral consequences for those who have been victims or are close to one. Measuring and evaluating this perception of insecurity becomes relevant as it is experienced as a feeling of vulnerability and lack of protection against the possibility of being a victim of crime, negatively affecting people's quality of life, either by impacting their routines, modifying their lifestyles, their relationship with others, among other consequences [24, 8]. Behavioral adaptations are observed in insecure situations. This behavior may vary according to the time of day or, more specifically, according to daylight and lighting conditions. These measures can be passive by distancing oneself in space and time from potential aggressors, modifying travel patterns, destinations or routes [44, 31]. In some cases, it can reach an extreme case of self-confinement, turning individuals into "prisoners in their own homes" [20, 8]. From a public policy perspective, the restriction in mobility that can result from high levels of insecurity is of particular relevance as it affects the way in which citizens can benefit from the services and opportunities offered by urban life. Although fear and personal insecurity are present throughout society, certain categories of people are or feel more vulnerable [44]. Individual factors play an important role in defining the risk of victimization, as well as in the general perception of safety [8]. Previous victimization (or knowledge of others' victimization) is often considered a determinant of a person's fear, although research findings may be contradictory [19, 37], since in more vulnerable groups, the rate of victimization is lower (for example, although women may be more vulnerable to being victims of crime, they have a lower rate of victimization than men). The individual dimension of fear is often related to the vulnerability hypothesis, i.e., those who perceive themselves as vulnerable are likely to be more fearful. Traditionally, women are depicted as more fearful of their personal safety (particularly in public places) than men [4, 27, 30, 8].

A specific element of women's perceived insecurity and habit changes compared to men is strongly linked to crime victimization, as they are generally socially and physically more vulnerable to crime, as they tend to have less physical strength and less ability to fight back [42, 44]. The literature points out that women's greater fear of crime, compared to men, can be largely explained by the fear of being a victim of a sexual crime, this is the "shadow sexual assault hypothesis" [12, 38, 22, 33]. At the same time, a greater sense of insecurity in women is determined by the characteristics of the physical environment and the residential neighborhood [3]. Mechanisms linking visible deterioration to fear of a place can be linked to the theory of incivilities [28] or broken windows [25] suggesting that disorder, property damage and neglect encourage more vandalism and other types of crime [29]. This fear is associated with behavioral changes or responses that limit people's activities when they perceive specific places or areas as unsafe [35]. Sociodemographic factors such as income and age are also related to women's perception of insecurity, limiting their relationship with their environment [32, 44, 45].

In this paper we study the relationship between the feeling of insecurity and mobility of people, differentiating this relationship by gender, in the city of Santiago, Chile. As a result of the greater physical vulnerability and the specific threat posed by crimes of a sexual nature, the daily geographies of men and women are different in terms of lifestyles, mobility and behavior in the city. Specifically, it has been observed that women restrict their movements around the city to minimize their perception of insecurity and fear in public spaces [40]. Women tend to avoid certain destinations or routes and modes of travel more than men. Women in general have restricted travel behavior due to fear for their personal safety [44]. In this situation, the focus is not necessarily on victimization by serious crimes, but on situations such as sexual harassment. For women in particular, sexual harassment and other forms of sexual violence in public spaces are everyday occurrences that affect their perception of safety in transit [14, 36].

From a methodological perspective, the novelty of our study lies in the use of mobility measures constructed from digital traces of mobile devices from a telephone company with high penetration levels. Studying and characterizing people's mobility from digital traces is a source of data on human behavior and interactions between people [2]. The use of mobile devices has made it possible to explore the mobility of people and their patterns in the city on a larger scale [15, 5, 1, 16, 39, 13]. Given the high penetration rates of their use, mobile devices also allow to study the aggregate behavior of people within a territory, since their traces contain the location of the places visited by a person [23] and avoid the biases of origin-destination surveys, a standard source for traditional mobility studies. Using this approach, and computing two measures of mobility, number of trips and their entropy, Gauvin *et al* [13] observe a gender gap in the urban area of the city of Santiago, Chile: women visit fewer unique locations than men and distribute their time less regularly among those locations.

Women in general, due to the fear of being a victim of crime, have a restricted travel behavior [44, 8, 7, 9, 21, 41]. According to the 2017 National Urban Survey on Citizen Safety (ENUSC[1] survey), in the city of Santiago, 72% of women avoid streets, 79% and 70% avoid neighborhood squares and sports courts, respectively, and 45% avoid bus stops, these frequencies being significantly higher compared to men. A study conducted in Vienna shows that 75% of women previously affected by a frightening situation and 60% of unaffected women avoid certain routes and destinations as a safety precaution in their daily mobility, such as public spaces with dim lighting, deserted streets and places, city centers and parks, among others [44]. In Stockholm, the impact of fear on mobility and precautionary behavior of young people was investigated. where previous victimiza-

[1] In Spanish: Encuesta Nacional Urbana de Seguridad Ciudadana. In this study we will refer to it as ENUSC.

tion, especially for sexual offenses, triggers precautionary behavior for users in transport systems, mainly subway or trains, but not in those who take buses, where 50% of women took precautionary measures in these means compared to 24% of men [8].

To study the extent to which insecurity explains this gap, we computed measures of insecurity from the ENUSC survey, an instrument developed and implemented by the National Institute of Statistics of Chile. Specifically, we constructed an indicator of emotional, cognitive and evaluative insecurity. The emotional factor refers to fear of dangerous situations or places; the cognitive factor is linked to a person's analysis, which, based on personal and contextual variables, estimates the probability of being a victim of crime; and the evaluative factor, of a more political nature, measures the perception of crime as a social problem [26]. The emotional dimension of insecurity was measured in different urban contexts: buses, bus stops, subway, collective taxis, neighborhood squares and parks, neighborhood sports courts, and streets. The feeling of insecurity can also be the result of what one sees and perceives with the other senses, which means that fear is a function of an individual's emotional reactions to a place at a particular time and/or memories and associations brought about by a particular environment. Therefore, if one is exposed to certain crime-prone locations, this can also lead to higher levels of fear.

Hypothesis

1. As insecurity impacts routines and lifestyles to avoid the risks of crime and violence, it is expected that higher levels of insecurity will result in lower levels of mobility.
2. Associated with the higher level of vulnerability of women, it is expected that there is a stronger relationship between insecurity and mobility than in men.
3. As a result of the "shadow of sexual assault" effect, it is expected that the relationship between insecurity and mobility will be stronger in those places where the perception of insecurity in the face of sexual crimes is greater.

Our results support the proposed hypotheses. First, they show that there is a negative and significant relationship between insecurity and mobility, which would imply that people's mobility would decrease in the face of a greater perception of insecurity. Although this relationship is observed for both sexes, it is observed more strongly in women, who are the ones who reduce their mobility habits even more than men, mainly in places such as bus stops, squares, parks and neighborhood sports courts, and the street. Women are observed to be less mobile than men, with average differences for entropy and number of trips, respectively, of 0.13 and 6.25 at bus stops, 0.15 and 6.09 in squares and parks, 0.11 and 5.19 in sports courts, and 0.16 and 7.18 in the street. The reduction in mobility, given an increase of one percentage point of insecurity, also presents a gap, with this reduction being greater for women. Respectively, for entropy and number of trips, this difference is 0.42 and 11.84 at bus stops, 0.27 and 7.90 in squares and parks, 0.21 and 6.10 in sports courts, and 0.23 and 5.54 in the street.

2.2 Data and Methods

2.2.1 Data

Two sources of information were used. First, the 2017 National Urban Survey on Citizen Security of the National Institute of Statistics (INE, Chile) was used to generate the insecurity indicators. Its objective is to obtain information on the perception of insecurity, reaction to crime and victimization of individuals and households, based on a representative sample of urban areas at the national and regional levels. Second, to measure and evaluate mobility, anonymized and aggregated mobile telephone records from Telefónica Chile were used.

The unit of analysis for the research was the commune. In Chile, communes are the smallest administrative units. There are 346 communes in the country, 52 of which are located in the Metropolitan Region. This region concentrates 40.5% of the population according to the 2017 Population and Housing Census. The study was conducted in the city of Santiago, belonging to the Metropolitan Region, which has 34 communes[2].

2.2.1.1 Insecurity

The ENUSC survey was conducted between September and December 2017 in a sample of 27,616 households. Its target population is households and individuals aged 15 years old or older residing in urban areas. Its observed absolute error is 0.85 at the national level and an average of 2.91% at the regional level. Based on this, we worked with a sample of 18,191 people residing in the city of Santiago, divided into 8,599 men and 9,592 women.

From the ENUSC survey we generated indicators for the three factors that allow us to understand the perception of insecurity: emotional, cognitive and evaluative.

The emotional factor was constructed from the question that measures the feeling of insecurity in different places. This question has four response categories: very insecure, insecure, secure and very secure. We classified as insecure those observations whose response was very insecure or insecure. We worked with the places related to a change in behavior associated with people's daytime mobility as a consequence of perceived insecurity. These are buses, collective taxis[3], subway, neighborhood squares and parks, neighborhood sports courts, bus stops and the streets[4]. To measure the emotional factor,

[2] Cerrillos, Cerro Navia, Conchalí, El Bosque, Estación Central, Huechuraba, Independencia, La Cisterna, La Florida, La Granja, La Pintana, La Reina, Las Condes, Lo Barnechea, Lo Espejo, Lo Prado, Macul, Maipú, Ñuñoa, Pedro Aguirre Cerda, Peñalolén, Providencia, Pudahuel, Puente Alto, Quilicura, Quinta Normal, Recoleta, Renca, San Bernardo, San Joaquín, San Miguel, San Ramón, Santiago y Vitacura.

[3] In Chile, collective taxis is a service that only attends trips with a previously established route. It is identified by the color black and by the sign that must be placed on the roof of the vehicle indicating the service and the route.

[4] The ENUSC survey asks about the feeling of insecurity in thirteen places, plus three situations when it is already dark. The question, related to the feeling of insecurity in different places is: During the last 12 months, according to your experience, how do you feel in the following places?: your place of work, your place of study, buses, collective taxis, subway (Metro de Santiago, Merval, Biotrén, Metrotrén), shopping centers or malls, stadiums, ATMs available on public roads with no time restriction for access, neighborhood squares and parks, sports courts in your neighborhood, bus stops in your neighborhood, streets in your neighborhood and bus terminals. The question related to insecurity when it is dark is: how safe do you feel in the following situations when it is dark?: walking alone in your neighborhood, alone at home and waiting for public transportation.

an aggregate indicator of insecurity was constructed as the sum of the insecurity perceived in the seven places identified, as well as an individual indicator for each of these. Although the aggregate indicator corresponds to the sum of insecurities (with a maximum of seven and a minimum of zero), it was constructed as a percentage (seven insecurities corresponds to 100%) to make it comparable with the cognitive and evaluative factors.

The cognitive factor was constructed from a single question, referring to the belief of being a victim of a crime in the next twelve months, with two response categories: yes or no.

Finally, the evaluative factor was constructed with the question that measures the perception of an increase or decrease in crime during the last twelve months. This question is asked at the level of three territories: country, commune and neighborhood, and has three possible response categories: increased, remained the same or decreased. We classify as insecure observations whose response is increased. Similarly, to measure the evaluative factor, an aggregate indicator of insecurity was constructed as the sum of the perception of increase in the country, the commune and the neighborhood, as well as an individual indicator for each of these three territories. Although the aggregate indicator corresponds to the sum of insecurities (with a maximum of three and a minimum of zero), it was constructed as a percentage (three insecurities corresponds to 100%) to make it comparable to the emotional and cognitive factors.

This perception of insecurity, at the emotional, cognitive and evaluative levels, is answered by men and women, and is therefore measured and differentiated by gender.

2.2.1.2 Mobility

Mobility was assessed based on the indicators of Gauvin *et al.* [13], which was quantified from anonymized and aggregated cell phone records from 2016, specifically for the months of May, June and July. This set of anonymized mobile telephone records or CDRs contains information on gender, nationality, socioeconomic segment and number of telephone lines registered and associated with a certain telephone number. Based on an identifiable location (home address) and with more than two different locations during three months, we worked with 418,624 unique users, 51% of whom were women. Two gender-differentiated mobility metrics, number of trips and entropy, were used [23, 13].

The number of trips corresponds to the number of locations or places a person has visited. When a cellular device interacts with the network there is a record of its connection to the antenna and when this took place. We consider as a trip the passage from one antenna to another. For two geographic territories, A and B, we get that the number of trips from A to B is estimated as the sum of the trips between antennas inside A and antennas inside B. It is important to note that these records do not give the exact location of the devices but the antenna to which it was connected.

Entropy, on the other hand, measures the diversity of individual mobility. It measures Shannon's entropy of a user's trajectories as:

$$S = -\sum_{l \in L} p_l \ln p_l \tag{2.1}$$

where L is all locations visited by a user, and p_l is the probability of observing a user at location l, calculated as the fraction of calls made by the user at the location l [13]. Accordingly, for a user with a high entropy it is concluded that they distribute their trips in many different locations with the same probability, while for a user with a lower entropy a higher regularity of their mobility patterns will be concluded, in a smaller set of regularly visited locations [43, 23, 13].

2.2.1.3 Dictionary of variables

According to the sources of information described, the study variables defined were:

1. *Emotional insecurity:* mean, by gender, of the number of places where people feel insecure.
2. *Emotional insecurity i:* percentage of people, by gender, who feel insecure in the place i (where i is: buses, collective taxis, subway, neighborhood squares and parks, neighborhood sports courts, bus stops, and streets).
3. *Cognitive insecurity:* percentage of people, by gender, who believe they will be victims of crime.
4. *Emotional insecurity:* mean, by gender, of the number of areas where people believe that crime has increased.

2.2.2 Method

The method considers a descriptive and inferential bivariate analysis to evaluate the relationship between the relevant variables, mobility and insecurity. A t-test was used to compare the means by gender. The indicator used to evaluate the relationship was Pearson's linear correlation index. For explanatory purposes and to evaluate causality, the functional relationship between mobility and insecurity was modeled. The technique used for modeling was linear regression [17, 18]. In its simple form, where $Y = Mobility$ y $X = Insecurity$, we get:

$$Y = \beta_0 + \beta_1 X$$

But this relationship only allows us to evaluate the relationship and dependence between the two variables, our purpose being to identify a gap in the relationship by gender. Accordingly, we expand our model to a more complex form, where $X = Insecurity$ y $D = Female$, with D being a dummy variable that takes the value 1 when female and zero if male:

$$Y = \beta_0 + \beta_1 X + \beta_2 D + \beta_3 XD$$
$$Y = \beta_0 + \beta_2 D + (\beta_1 + \beta_3 D) X$$

In this case, we see that the X slope contains two components $\beta_1 + \beta_3 D$. When D is equal to 0, the slope is β_1. However, when D is equal to 1, the slope is equal to the algebraic sum of $\beta_1 + \beta_3$. Therefore, for the case of evaluating differences in the mobility and insecurity relationship between men and women, the model including differences between the slope coefficients and constants, for women is:

$$Y = (\beta_0 + \beta_2) + (\beta_1 + \beta_3)X_1$$

And for men:

$$Y = \beta_0 + \beta_1 X_1$$

Therefore, β_2 corresponds to the difference in the average mobility of women with respect to men when insecurity is equal to zero, and β_3 corresponds to the difference in the increase in mobility for each percentage point that insecurity increases for women with respect to men. If we think that gender does not influence mobility, the parameters that measure this difference between men and women must be statistically equal to zero, i.e. $\beta_2 = \beta_3 = 0$, otherwise, we would have sufficient evidence to conclude that gender does influence mobility. Under the null hypothesis that gender does not influence the relationship between mobility and insecurity ($\beta_2 = \beta_3 = 0$), with respect to an alternative hypothesis that the relationship between mobility and insecurity is gender dependent (at least one of the two parameters is non-zero), by rejecting the null hypothesis we would have statistical evidence to conclude that gender does influence both variables. A joint hypothesis test was used to evaluate the statistical significance of the parameter of the variable associated with gender, as well as the interaction of this quality with insecurity [17, 6]. The significance of both parameters allows us to conclude that gender influences the relationship between mobility and insecurity.

2.3 Results

2.3.1 Description of insecurity

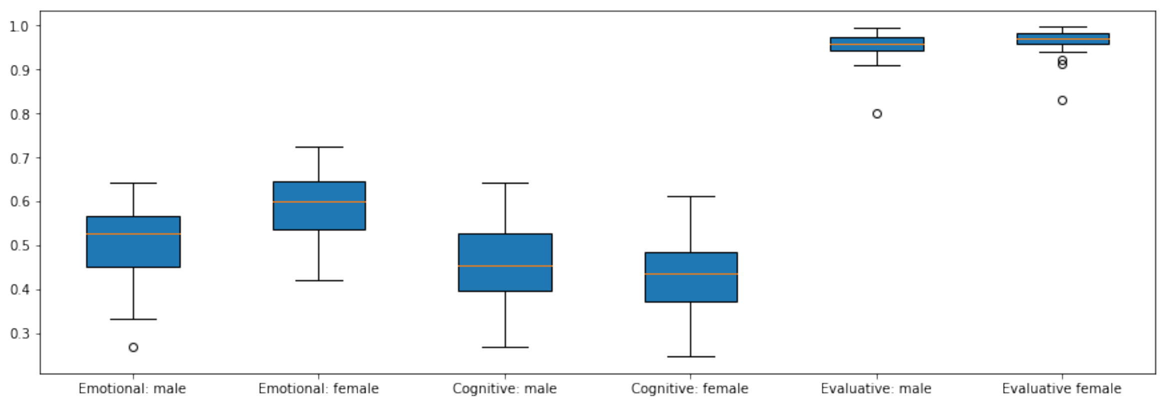
The differences by gender in insecurity are presented in Table 2.1. Out of the three dimensions, the emotional factor is the only one that shows significant differences ($p < 0.01$) where 59% of women report feeling insecure in some place, as opposed to men, where only 50% express this feeling.

Table 2.1: Means difference in insecurity by gender

Factor	Male	Female	Differences
Emotional	0.50	0.59	0.09^{a}
Cognitive	0.46	0.43	0.03
Evaluative	0.95	0.97	0.02

x^a differences statistically significant $p < 0.01$.

Figure 2.1: Distribution of insecurity by gender.



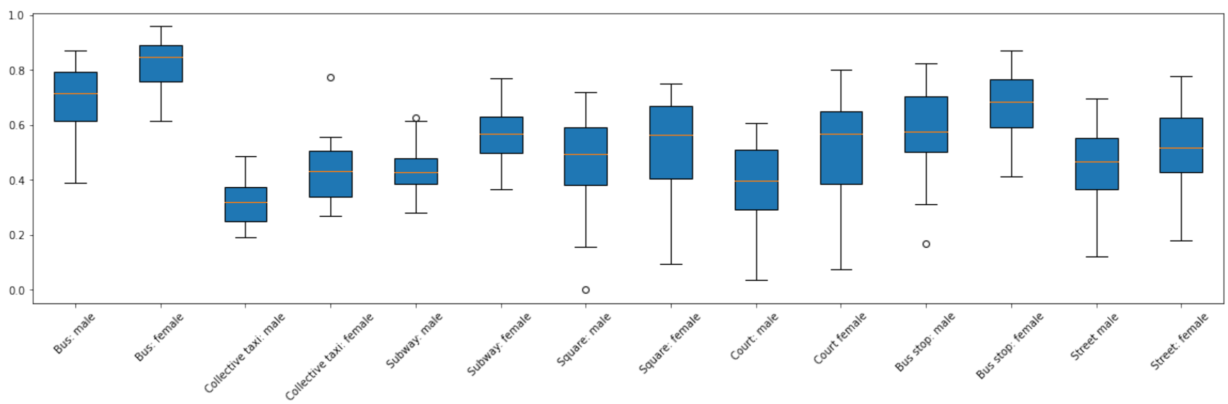
Since the emotional factor is the only one that shows significant differences between men and women, we worked and disaggregated this indicator into the seven places from which it was constructed. Table 2.2 shows the percentage of people, by gender, who feel unsafe on a bus, in a taxi-bus, in the subway, in neighborhood squares and parks, in neighborhood sports courts, at bus stops and on the street. These differences are significant in buses, collective taxis, subways, and neighborhood sports courts ($p < 0.01$), as well as at bus stops ($p < 0.05$). It is important to note that, although no statistical differences are observed in neighborhood squares and parks, as well as in the street, this does not imply that men and women do not feel insecure in these places, only that a difference by gender is not observed.

Table 2.2: Means difference in emotional factor by gender.

	Male	Female	Differences
Buses	0.70	0.83	0.12^a
Collective taxis	0.32	0.43	0.11^a
Subway	0.44	0.56	0.12^a
Neighborhood square	0.47	0.53	0.06
Neighborhood sport court	0.38	0.50	0.12^a
Bus stop	0.58	0.67	0.09^b
Street	0.45	0.51	0.06

x^a differences statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Figure 2.2: Insecurity distribution by gender.



2.3.2 Description of mobility

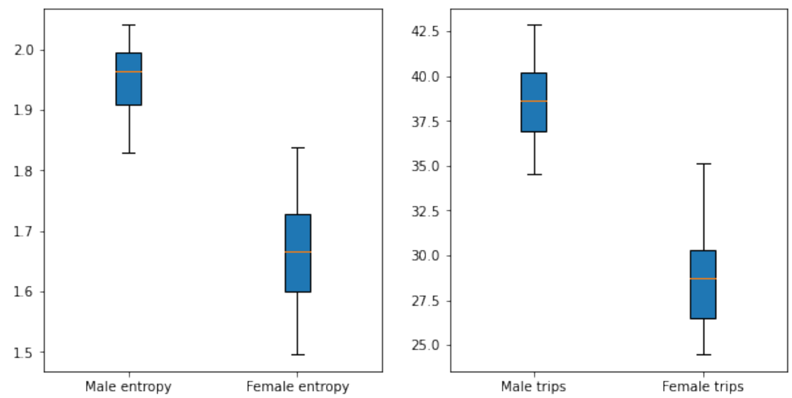
Men have greater mobility than women. On average, an entropy of 1.95 for men and 1.67 for women is observed, as well as a mean of 38.64 and 28.94 trips, respectively (Table 2.3). Significant differences ($p < 0.01$) were observed in both cases. Since both indicators are different units of measurement, the difference is also presented as a rate (ratio). The magnitude of this difference is greater in trips, where men present an average 33.5% higher than women, in contrast to entropy where it is only 16% higher. Figure 3.4 shows distributions for both mobility indexes.

Table 2.3: Means difference in mobility by gender.

	Male	Female	Differences	Difference rate
Entropy	1.95	1.67	0.28^a	16.77%
Trips	38.64	28.94	9.70^a	33.52%

x^a differences statistically significant $p < 0.01$.

Figure 2.3: Mobility distribution by gender.



2.3.3 Relationship between insecurity and mobility

A negative correlation between mobility and insecurity. For the emotional factor of insecurity, significant relationships are observed in both genders. Men present a correlation of -0.38 with entropy ($p < 0.05$) and -0.46 with the number of trips ($p < 0.01$). On the other hand, women present an adjustment of -0.67 with entropy ($p < 0.01$) and -0.70 with the number of trips ($p < 0.01$). Regarding the cognitive and evaluative factor, only women show a significant relationship with their mobility ($p < 0.01$). In the cognitive dimension, a correlation of -0.57 is observed for entropy and -0.66 with the number of trips, and -0.54 and -0.64 for the evaluative dimension, respectively. Accordingly, a linear association between mobility and insecurity is observed, being this relationship significant for women, and stronger with the number of trips (Table 2.4).

Table 2.4: Correlation between mobility and insecurity.

	Male entropy	Female entropy	Male trips	Female trips
Emotional	-0.38^b	-0.67^a	-0.46^a	-0.70^a
Cognitive	-0.19	-0.57^a	-0.42^b	-0.66^a
Evaluative	-0.17	-0.54^a	-0.29	-0.64^a

x^a correlations are statistically significant at $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Table 2.5 shows the correlation of each of the places that make up the emotional factor with mobility. In the case of men, although significant relationships are observed, mainly with the number of trips, these present a low adjustment. This is not the case for women, who present negative and significant correlations ($p < 0.01$) in both mobility measures, being the relationship with the number of trips the one that presents the highest adjustments. For women, these correlations with entropy and number of trips, respectively, are -0.64 and -0.68 in buses, -0.78 and -0.83 in neighborhood squares and parks, -0.68 and -0.79 in neighborhood sports courts, -0.78 and -0.82 in bus stops, and -0.64 and -0.67 in streets. This result implies that women reduce their mobility when faced with a greater perception of insecurity in these places.

Table 2.5: Correlation between mobility and emotional insecurity (locations).

	Male entropy	Female entropy	Male trips	Female trips
Buses	-0.35^b	-0.64^a	-0.43^b	-0.68^a
Collective taxis	-0.20	0.02	-0.17	0.02
Subway	-0.26	-0.30	-0.35^b	-0.35^b
Neighborhood square	-0.42^b	-0.78^a	-0.49^a	-0.83^a
Neighborhood sport court	-0.28	-0.68^a	-0.37^b	-0.79^a
Bus stops	-0.34	-0.78^a	-0.45^a	-0.82^a
Street	-0.37^b	-0.64^a	-0.47^a	-0.67^a

x^a correlations are statistically significant at $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Although women present a better fit between mobility and their perception of insecurity, we evaluate the dependence and differences in the relationship between men and women. Table 2.6 and Table 2.7 present the models for entropy and number of trips, respectively.

Insecurity and its interaction with gender in collective taxis and the subway do not present significant parameters, which indicates that the perception of insecurity in these means of transportation and gender do not affect the mobility of men and women.

On the other hand, in the buses, bus stops, neighborhood squares and parks, neighborhood sports courts and in the streets, at least one significant (non-zero) parameter is observed, either the parameter of the dummy variable associated with gender or that of its interaction with insecurity. This is evidence of a gender gap. The negative parameter of the gender dummy implies that women are less mobile than men, and the negative parameter of its interaction with insecurity implies that women reduce their mobility more than men when faced with the same level of insecurity.

Table 2.8 presents the results of the joint hypothesis test to evaluate the significance of the parameters of the dummy variable associated with gender, as well as how this quality interacts with insecurity. Under the null hypothesis that gender does not influence the relationship between mobility and insecurity ($\beta_2 = \beta_3 = 0$), and according to the observed p-values, the test provides statistical evidence ($p < 0.01$) to conclude that gender does influence the relationship between mobility and insecurity, observing a difference in the relationship between men and women, and therefore a gender gap in the relationship between mobility and insecurity.

Table 2.12 and Table 2.13 of the supplementary material present, as a measure of robustness, the inference performed with bootstrapping and a Bayesian approach to validate our results. For each model, the parameters are presented with interval estimates considering 95% confidence. Each mobility measure is presented in terms of total emotional insecurity and perceived insecurity in the seven locations assessed. The bootstrapping estimates and the Bayesian approach do not differ from the confidence intervals constructed by Least Squares. Except for five specific cases, these approaches generate confidence intervals that make the parameters significant, validating the gender gap for entropy and number of trips.

We observe that gender alone does not explain and differentiate mobility patterns between men and women. One of the factors that would explain it and generate a gender gap is insecurity. This feeling would generate a change in behavior patterns in both men and women, but it is the latter, faced with the same level of insecurity, who further reduce their mobility, measured as entropy as well as the number of trips. This greater reduction in mobility among women is observed when evaluating the emotional factor of insecurity (aggregate measure), as well as when evaluated in terms of perceived insecurity on buses, bus stops, neighborhood sports courts, neighborhood squares and parks, and in the streets. No differences were observed in the subway and collective taxis.

Table 2.6: Modeling, dependent variable: Mobility (entropy).

	Emotional insecurity	Buses insecurity	Bus stops insecurity	Sport court insecurity	Square insecurity	Street insecurity	Subway insecurity	Collective taxis insecurity
Intercept	2.07^a	2.08^a	2.03^a	1.99^a	2.02^a	2.02^a	2.04^a	2.00^a
	(0.06)	(0.07)	(0.04)	(0.03)	(0.03)	(0.04)	(0.07)	(0.06)
Female	0.02	0.11	0.01	-0.17^a	-0.13^a	-0.16^a	-0.21	-0.34^a
	(0.10)	(0.12)	(0.07)	(0.04)	(0.04)	(0.06)	(0.11)	(0.08)
Emotional	-0.23^b							
	(0.11)							
Emotional x Female	-0.49^a							
	(0.17)							
Buses insecurity		-0.18						
		(0.10)						
Buses insecurity x Female		-0.46^a						
		(0.16)						
Bus stops insecurity			-0.13					
			(0.07)					
Bus stops insecurity x Female			-0.42^a					
			(0.10)					
Neighborhood sport court insecurity				-0.11				
				(0.07)				
Neighborhood sport court insecurity x Female				-0.21^b				
				(0.09)				
Neighborhood square insecurity					-0.15^b			
					(0.06)			
Neighborhood square insecurity x Female					-0.27^a			
					(0.08)			
Street insecurity						-0.16		
						(0.08)		
Street insecurity x Female						-0.23^b		
						(0.11)		
Subway insecurity							-0.20	
							(0.16)	
Subway insecurity x Female							-0.10	
							(0.22)	
Collective taxis insecurity								-0.16
								(0.18)
Collective taxis insecurity x Female								0.17
								(0.22)
R-squared	0.86	0.85	0.88	0.86	0.89	0.85	0.80	0.78
R-squared Adj.	0.85	0.85	0.88	0.85	0.88	0.85	0.79	0.77
N	68	68	68	68	68	68	68	68

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Table 2.7: Modeling, dependent variable: Mobility (number of trips).

	Emotional insecurity	Bus insecurity	Bus stop insecurity	Sport court insecurity	Square insecurity	Street insecurity	Subway insecurity	Collective taxis insecurity
Intercept	43.73^a	44.14^a	42.29^a	40.63^a	41.47^a	41.85^a	42.73^a	40.16^a
	(1.83)	(2.15)	(1.25)	(0.91)	(0.88)	(1.20)	(2.32)	(1.88)
Female	-1.01	2.26	-1.26	-6.00^a	-5.15^a	-6.39^a	-7.86^b	-11.43^a
	(3.02)	(3.84)	(2.08)	(1.28)	(1.32)	(1.74)	(3.43)	(2.63)
Emotional insecurity	-10.15^a							
	(3.59)							
Emotional insecurity x Female	-13.38^b							
	(5.42)							
Buses insecurity		-7.86^b						
		(3.02)						
Buses insecurity x Female		-13.28^a						
		(4.88)						
Bus stops insecurity			-6.25^a					
			(2.08)					
Bus stops insecurity x Female			-11.84^a					
			(3.20)					
Neighborhood sport court insecurity				-5.19^b				
				(2.21)				
Neighborhood sport court insecurity x Female				-6.10^b				
				(2.77)				
Neighborhood square insecurity					-6.09^a			
					(1.77)			
Neighborhood square insecurity x Female					-7.90^a			
					(2.51)			
Street insecurity						-7.18^a		
						(2.57)		
Street insecurity x Female						-5.54		
						(3.49)		
Subway insecurity							-9.34	
							(5.22)	
Subway insecurity x Female							-1.16	
							(6.83)	
Collective taxis insecurity								-4.81
								(5.80)
Collective taxis insecurity x Female								5.30
								(7.13)
R-squared	0.88	0.87	0.90	0.89	0.90	0.87	0.82	0.80
R-squared Adj.	0.87	0.86	0.89	0.88	0.90	0.86	0.81	0.79
N	68	68	68	68	68	68	68	68

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Table 2.8: Joint significance test.

Model	Null hypothesis	p-value (entropy)	p-value (trips)
Emotional insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Emotional * Female}} = 0$	0.0000	0.0000
Buses insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Buses * Female}} = 0$	0.0000	0.0000
Bus stops insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Bus stops * Female}} = 0$	0.0000	0.0000
Neighborhood sport court insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Sport court * Female}} = 0$	0.0000	0.0000
Neighborhood square insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Square * Female}} = 0$	0.0000	0.0000
Street insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Street * Female}} = 0$	0.0000	0.0000
Subway insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Subway * Female}} = 0$	0.0000	0.0000
Collective taxis insecurity	$\beta_{\text{Female}} = 0$ $\beta_{\text{Collective taxis * Female}} = 0$	0.0000	0.0000

2.4 Discussion and conclusions

Both men and women feel insecurity, but it is women who have a greater perception of this feeling (Table 2.1 and Table 2.2). When we relate this feeling of insecurity (emotional factor) to mobility, we observe a negative and significant relationship in both genders, only women show a stronger association between both variables (Table 2.4), which implies that their mobility is even more reduced when faced with the same feeling of insecurity. When we disaggregate emotional insecurity on buses, bus stops, neighborhood squares and parks, neighborhood sports courts, and in the streets, we see that men do not present a significant relationship between their entropy and the perception of insecurity and, although they do present it with the number of trips, the association, measured with Pearson's correlation index, is low. This is not the case for women who, both for their entropy and the number of trips, present a high degree of association with insecurity, except in the relationship perceived in the Collective taxis and in the subway (Table 2.5).

Women's insecurity and mobility restrictions are related not only to crime victimization, but also to the fear of being a victim of sexual assault [44, 8, 7, 9, 21, 41], this is the so-called "shadow of sexual assault hypothesis" [12, 38, 22, 33]. Given a perceived insecurity due to fear of a possible sexual assault, these results are related to the 2015 statistics of the Observatory Against Harassment in Chile[5] in the Metropolitan Region and the National Women's Service[6], SERNAM. SERNAM points out that street sexual harassment can be distributed according to its context in two categories: time and place. The service indicates that between 40% and 50% of sexual aggressions occur in buses, 20% and 30% in the street, and 15% and 20% in the subway. In the case of women, the Observatory Against Harassment in Chile indicates that the most frequent scenarios of street sexual harassment occur in the street (50%), in the bus (15%), in the subway (11%), in a square

[5]https://ocac.cl

[6]https://ocac.cl/wp-content/uploads/2015/01/SERNAM-Estudio-acoso-y-abuso-sexual-en-lugares-publico-y-mediosde-transporte.pdf

or park (6%), and in other means of transport and public places (18%).

A gender gap is observed when modeling the relationship between mobility and insecurity. For entropy and number of trips, it is observed that it is women, in response to a change in insecurity, who reduce their mobility the most, mainly on buses, bus stops, neighborhood squares and parks, neighborhood sports courts, and on the street (Table 2.6, Table 2.7, Table 2.8, Table 2.12 y Table 2.13).

We note that gender alone does not explain and differentiate mobility patterns. One of the factors that would explain it and generate a gender gap is insecurity. This feeling would generate a change in routines, habits and behavior, both in men and women, the latter being the ones who further reduce their mobility (entropy and number of trips). This greater reduction in mobility among women is observed when evaluating the emotional factor of insecurity (aggregate measure), as well as in buses, bus stops, neighborhood squares and parks, neighborhood sports courts, and on the streets. No differences were observed in the subway and collective taxis.

The results presented are evidence that allows us to validate our hypotheses since, for both genders, a reduction in mobility is observed in response to an increase in perceived insecurity, with women showing the strongest correlation. At the same time, the relationship is stronger in those places where the perception of insecurity regarding sexual crimes is higher.

Now, it is important to highlight the difference observed between entropy and the number of trips. In the case of men, their insecurity does not present significant relationships with entropy, but it does with the number of trips. In the case of women, although entropy and the number of trips present significant correlations, the number of trips always presents stronger associations, with Pearson correlation indexes close to 1. Our hypothesis to justify this difference lies in the definition of entropy and its interpretation, because if a user has a high entropy it can be inferred that he/she distributes his/her trips in many different locations with the same probability, while a user with a lower entropy has a greater regularity of his/her mobility patterns, in a smaller set of regularly visited locations [43, 13]. Women's mobility depends on a variety of contexts. In conceptualizing gender and mobility, it is essential to explore not only the factors related to relocation and its characteristics, but also aspects such as the allocation of roles within families [10]. Here we refer to those who perform domestic work. We believe that, in situations of insecurity, the number of trips can be modified, reducing or avoiding certain places, which translates into a significant reduction in the number of trips. Not so with entropy. If we associate this measure, for example, to a woman who performs domestic work, she must visit the same places every day: children's school, supermarket, among others, which cannot be avoided. Similarly, and not related to domestic work, a greater regularity, in a smaller set of visited locations, would also imply that women, regardless of their work or task, in the face of a high sense of insecurity, maintain and move to a smaller number of locations, just enough and necessary, reducing to a minimum the activities they must perform. These examples would relate to the definition and interpretation of entropy: "a lower entropy implies a greater regularity of their mobility patterns, in a smaller set of locations visited regularly".

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2.5 Supplementary material

2.5.1 Descriptive statistics

Table 2.9: Description of mobility rates by gender.

	Male entropy	Female entropy	Male trips	Female trips
count	34.00	34.00	34.00	34.00
mean	1.95	1.67	38.64	28.94
std	0.06	0.09	2.10	2.83
min	1.83	1.50	34.52	24.46
25%	1.91	1.60	36.90	26.52
50%	1.96	1.67	38.67	28.76
75%	2.00	1.73	40.17	30.33
max	2.04	1.84	42.86	35.16

Table 2.10: Description of insecurity factors by gender.

	Emotional: male	Emotional: female	Cognitive: male	Cognitive: female	Evaluative: male	Evaluative: female
count	34.00	34.00	34.00	34.00	34.00	34.00
mean	0.50	0.59	0.46	0.43	0.95	0.97
std	0.10	0.08	0.10	0.09	0.04	0.03
min	0.27	0.42	0.27	0.25	0.80	0.83
25%	0.45	0.54	0.40	0.37	0.94	0.96
50%	0.53	0.60	0.46	0.44	0.96	0.97
75%	0.57	0.65	0.53	0.49	0.97	0.98
max	0.64	0.72	0.64	0.61	1.00	1.00

Table 2.11: Description of the emotional factor (location) by gender.

	Buses: male	Buses: female	Collective taxis: male	Collective taxis: emale	Subway: male	Subway: female	Square: male	Square: female	Court: male	Court: female	Bus stops: male	Bus stops: female	Street: male	Street: female
count	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00	34.00
mean	0.70	0.83	0.32	0.43	0.44	0.56	0.47	0.53	0.38	0.50	0.58	0.67	0.45	0.51
std	0.12	0.09	0.08	0.11	0.08	0.09	0.17	0.17	0.15	0.20	0.15	0.13	0.14	0.15
min	0.39	0.61	0.19	0.27	0.28	0.37	0.00	0.09	0.04	0.08	0.17	0.42	0.12	0.18
25%	0.62	0.76	0.25	0.34	0.39	0.50	0.38	0.40	0.29	0.38	0.50	0.59	0.37	0.43
50%	0.72	0.85	0.32	0.43	0.43	0.57	0.50	0.56	0.40	0.57	0.58	0.69	0.47	0.52
75%	0.79	0.89	0.37	0.51	0.48	0.63	0.59	0.67	0.51	0.65	0.70	0.77	0.55	0.63
max	0.87	0.96	0.49	0.78	0.63	0.77	0.72	0.75	0.61	0.80	0.83	0.87	0.69	0.78

2.5.2 Model Robustness

Since we are working with aggregated data at the commune level, and our population corresponds to the 34 communes that make up the city of Santiago, we validated our results with the Bradley Efron [11] bootstrapping resampling method. This technique allows us to model and make inference from a resampling of the sample data and to make inference on a resampled data sample. For each model, 10,000 simulations or resamples with replacement were performed.

On the other hand, we performed a Bayesian regression, which is a linear regression approach where the statistical analysis is performed within the context of Bayesian inference. This approach is based on Bayes' theorem, and allows us to assume an a priori distribution for the unknown parameters of the model, allowing us to have explicit results for the a posteriori probability distributions of the parameters. It uses an iterative MCMC (Markov Chain Monte Carlo) method to obtain approximately the posterior distribution of the parameters in the model. For this modeling we use Stan, named after Stanislaw Ulam [34], one of the mathematicians who developed the Monte Carlo method. Stan[7] is a free and open source C++ program for Bayesian inference that can be run from the command line of different programming languages. We use PyStan for Python. For each model we performed 10,000 simulations with 4 strings.

For entropy, the model that depends on the perceived insecurity on the bus presents a difference in the confidence interval for the insecurity parameter estimated with bootstrap. This interval with the bootstrapping method presents negative limits, expressing a significance for this parameter ($p < 0.05$). which is not observed with OLS and the Bayesian approach. The model of entropy as a function of insecurity at the bus stop also shows differences. In this case, the insecurity parameter shows a difference with the Bayesian and bootstrapping approaches with respect to the OLS, as both yield significant estimates ($p < 0.05$). For perceived insecurity in the streets, a difference is also observed with the bootstrapping method, as it provides a significant parameter ($p < 0.05$) in contrast to OLS and the Bayesian approach.

In the case of the number of trips, only the model that is a function of perceived insecurity in the subway presents a difference, specifically the confidence interval for the insecurity parameter estimated with bootstrap. This interval, with the bootstrapping method, has negative limits. This implies a significance for that parameter ($p < 0.05$) not observed with OLS and the Bayesian approach.

[7] https://mc-stan.org/

Table 2.12: 95% confidence intervals for parameter estimates: OLS, Bootstrap and Bayesian (dependent variable: entropy).

		OLS		Bootstrap		Bayesian	
		Lower	Upper	Lower	Upper	Lower	Upper
Emotional insecurity	Intercept	1.95	2.19	1.97	2.15	1.95	2.19
	Emotional insecurity	-0.46	-0.00	-0.40	-0.05	-0.47	-0.01
	Female	-0.17	0.21	-0.13	0.18	-0.18	0.21
	Emotional insecurity x Female	-0.83	-0.14	-0.78	-0.22	-0.83	-0.14
Bus insecurity	Intercept	1.94	2.22	1.97	2.18	1.94	2.22
	Buses insecurity	-0.37	0.01	**-0.33**	**-0.03**	-0.38	0.01
	Female	-0.13	0.36	-0.09	0.35	-0.14	0.36
	Buses insecurity x Female	-0.77	-0.15	-0.74	-0.20	-0.77	-0.14
Bus stop insecurity	Intercept	1.95	2.11	1.95	2.09	1.95	2.11
	Bus stops insecurity	-0.27	0.00	**-0.25**	**-0.01**	**-0.27**	**-0.00**
	Female	-0.13	0.14	-0.10	0.12	-0.13	0.14
	Bus stops insecurity x Female	-0.63	-0.22	-0.61	-0.25	-0.63	-0.22
Neighborhood sport court insecurity	Intercept	1.93	2.06	1.94	2.04	1.93	2.06
	Neighborhood sport court insecurity	-0.26	0.04	-0.22	0.02	-0.26	0.04
	Female	-0.26	-0.08	-0.25	-0.08	-0.26	-0.08
	Neighborhood sport court insecurity x Female	-0.39	-0.02	-0.38	-0.05	-0.39	-0.02
Neighborhood square insecurity	Intercept	1.96	2.08	1.97	2.07	1.96	2.08
	Neighborhood square insecurity	-0.26	-0.03	-0.25	-0.05	-0.26	-0.03
	Female	-0.22	-0.05	-0.20	-0.05	-0.22	-0.05
	Neighborhood square insecurity x Female	-0.44	-0.11	-0.43	-0.14	-0.44	-0.11
Street insecurity	Intercept	1.95	2.10	1.97	2.07	1.95	2.10
	Street insecurity	-0.32	0.00	**-0.28**	**-0.04**	-0.33	0.00
	Female	-0.27	-0.05	-0.25	-0.06	-0.27	-0.05
	Street insecurity x Female	-0.45	-0.01	-0.43	-0.05	-0.45	-0.01
Subway insecurity	Intercept	1.89	2.18	1.92	2.16	1.89	2.18
	Subway insecurity	-0.52	0.13	-0.47	0.08	-0.52	0.13
	Female	-0.42	0.01	-0.41	0.01	-0.43	0.01
	Subway insecurity x Female	-0.53	0.33	-0.51	0.29	-0.52	0.34
Collective taxis insecurity	Intercept	1.89	2.12	1.91	2.10	1.89	2.12
	Collective taxis insecurity	-0.52	0.20	-0.48	0.15	-0.53	0.20
	Female	-0.51	-0.18	-0.58	-0.16	-0.51	-0.18
	Collective taxis insecurity x Female	-0.27	0.61	-0.28	0.77	-0.26	0.63

Table 2.13: 95% confidence intervals for parameter estimates: OLS, Bootstrap and Bayesian estimates (dependent variable: number of trips).

		OLS		Bootstrap		Bayesian	
		Lower	Upper	Lower	Upper	Lower	Upper
Emotional insecurity	Intercept	40.07	47.39	39.32	47.69	40.06	47.46
	Emotional insecurity	-17.31	-2.98	-17.52	-1.99	-17.43	-2.89
	Female	-7.05	5.02	-8.04	6.02	-7.18	5.03
	Emotional insecurity x Female	-24.20	-2.56	-25.43	-1.55	-24.26	-2.34
Bus insecurity	Intercept	39.86	48.43	39.24	48.29	39.81	48.43
	Buses insecurity	-13.90	-1.82	-13.62	-1.23	-13.91	-1.79
	Female	-5.41	9.92	-5.68	11.21	-5.32	9.95
	Buses insecurity x Female	-23.02	-3.53	-23.99	-3.56	-23.05	-3.67
Bus stop insecurity	Intercept	39.78	44.79	39.07	44.60	39.77	44.84
	Bus stops insecurity	-10.41	-2.09	-10.03	-1.27	-10.49	-2.08
	Female	-5.41	2.89	-5.60	2.96	-5.48	2.94
	Bus stops insecurity x Female	-18.24	-5.45	-18.26	-5.47	-18.35	-5.36
Neighborhood sport court insecurity	Intercept	38.82	42.45	38.31	42.63	38.85	42.46
	Neighborhood sport court insecurity	-9.61	-0.77	-9.36	-0.31	-9.64	-0.89
	Female	-8.56	-3.45	-8.88	-2.92	-8.58	-3.48
	Neighborhood sport court insecurity x Female	-11.63	-0.58	-12.10	-0.70	-11.55	-0.54
Neighborhood square insecurity	Intercept	39.72	43.22	39.24	43.61	39.7	43.22
	Neighborhood square insecurity	-9.63	-2.55	-10.24	-1.93	-9.6	-2.53
	Female	-7.79	-2.52	-8.01	-2.24	-7.79	-2.46
	Neighborhood square insecurity x Female	-12.93	-2.88	-13.17	-2.62	-13.01	-2.93
Street insecurity	Intercept	39.45	44.25	39.19	44.31	39.49	44.28
	Street insecurity	-12.32	-2.04	-12.09	-1.94	-12.39	-2.07
	Female	-9.86	-2.92	-10.36	-2.25	-9.9	-2.98
	Street insecurity x Female	-12.51	1.43	-12.97	1.47	-12.39	1.51
Subway insecurity	Intercept	38.09	47.37	38.99	46.77	38.15	47.41
	Subway insecurity	-19.76	1.08	**-17.84**	**-1.17**	-19.84	0.87
	Female	-14.71	-1.02	-13.70	-1.48	-14.81	-1.11
	Subway insecurity x Female	-14.80	12.48	-12.89	9.80	-14.64	12.59
Collective taxis insecurity	Intercept	36.39	43.92	36.95	43.63	36.3	43.9
	Collective taxis insecurity	-16.40	6.78	-15.21	5.07	-16.33	7.09
	Female	-16.68	-6.18	-18.31	-6.00	-16.7	-6.09
	Collective taxis insecurity x Female	-8.94	19.54	-8.64	23.42	-9.27	19.56

3. Mobility and domestic violence against women in the city of Santiago, Chile

The issue of violence against women has gained increasing attention in recent years. Determining the factors that contribute to women becoming victims of violence is a significant challenge for society. Within a familial context, control over decision making and mobility have been linked to an increased risk of domestic violence. This study aims to examine the relationship between domestic violence and mobility among women. Utilizing police records as a measure of physical and psychological domestic violence and mobile phone data to define mobility in terms of entropy and number of trips, our findings reveal a negative correlation and a causal relationship between domestic violence and mobility, with domestic violence being a determinant of mobility among women. Education and employment status were found not to be protective factors. These results have implications for the design of public policies and interventions aimed at reducing and eliminating domestic violence against women, highlighting the need for further research on the associated variables.

3.1 Introduction

Violence against women is a social phenomenon that has been studied from evolutionary, social and ecological perspectives. For the World Health Organization (WHO), violence against women represents a serious public health problem and a violation of women's human rights [38, 39], since they are exposed to various forms of violence: physical, psychological, sexual and economic. This social phenomenon has increased in recent years [16]. In 2019, one in three women in the world suffered violence at some point in their lives[1]. According to the Undersecretary of Crime Prevention in Chile, in 2019, domestic violence against women increased by 7.5% compared to 2018.

Violence generates psychological consequences in women who have been victims, creating a feeling of vulnerability and lack of protection. This fear has the power to modify behavior and possibly restrict activities in women's daily lives, such as their mobility [35, 10]. Female mobility depends on a variety of contexts that are not strictly related to transportation systems [14]. There are factors on a community, household, and individual level, such as family role assignments, that determine women's ability to make decisions about their mobility [14]. Women's mobility patterns are different from men's, and in their daily commute they visit fewer places than men [45, 22]. This is because they spend more time on domestic work and childcare, so they tend to make fewer or shorter trips [47, 14, 22].

Control of female mobility is observed from two perspectives; control of the partner, and control of the woman herself. There are negative attitudes and controlling behaviors of partners towards female mobility. For example, their work outside the household may be conditioned, as it may depend on having work schedules and workplaces that allow them to continue with their domestic responsibilities. The level of control exercised by partners over female mobility and daily activities varies, with some cases escalating to situations of domestic violence if the woman refuses to change her occupational decisions [37, 14]. On the other hand, women can make their own decisions under an "agency" approach and achieve their life goals, including freedom from domestic violence and physical mobil-

[1] https://news.un.org/en/story/2019/11/1052041

ity [37, 14]. Domestic violence may not only be a barrier to women choosing to move, but also to accessing better economic opportunities [37, 14, 42]. In this context, agency is defined as empowerment [37] and female economic independence would be related to their mobility and to the possibility of being victims of violence [7]. In an economic independence approach, the phenomenon of violence against women and its causes have been described in terms of personal, psychological or socioeconomic characteristics of both the victim and the aggressor. Female personal characteristics, such as education and employment, are conditioning factors for violence against women [7, 33]. The United Nations International Children's Emergency Fund (UNICEF) points out that women's limited access to education increases the likelihood of suffering violence [36], education being a protective factor [51, 20, 2, 49]. Regarding employment, there is no consensus on how women who suffer violence are affected by their entry into the labor market [30, 11, 49]. Although women's access to employment would reduce the possibility of being a victim of domestic violence, the risk is conditioned by their partner's employment status [6]. Female participation in the labor force reduces the risk of domestic violence when her partner is also employed, but increases the risk of violence when he is not [30]. Women's employment provides independence and economic autonomy, as well as being a protective factor, since it reduces isolation and the hours women spend at home [21, 13, 6, 19].

Particularly, the present study is an exploratory analysis that examines the relationship between female mobility and domestic violence against women in the city of Santiago of Chile. Methodologically, the novelty of our study lies in the use of mobility measures constructed from digital traces of mobile devices from a telephone company with high penetration levels. Studying and characterizing the mobility of people from digital traces is a source of data on human behavior and interactions between people [8], allowing us to explore, on a larger scale, human trajectories with a high degree of temporal and spatial regularity [24, 24, 9, 5, 25]. Mobile devices allow for the study of the aggregate behavior of people within a territory, since digital traces contain the location of the places visited by a person, avoiding the biases of origin-destination surveys [22], a traditional source of mobility studies. Using this approach, and computing two gender-differentiated mobility measures, entropy and number of trips, Gauvin *et al* [22] observed a gender gap in the urban area of the city of Santiago of Chile, concluding that women visit fewer unique places than men, distributing their time less regularly among these places. To assess the extent to which domestic violence against women affects their mobility, we calculated two dimensions from geolocalized police cases: physical and psychological violence. In Chile, violence against women is concentrated in the family environment. It is a kind of domestic violence divided in two dimensions: physical and psychological. The Chilean National Service for Women and Gender Equity (SernamEG) defines physical violence as any type of physical aggression against women, the strongest form of physical aggression being femicide (in this research we do not consider femicide as physical violence). On the other hand, psychological violence refers to actions that attempt to control a woman with the purpose of making her feel insecure and without control over her life and decisions. In the city of Santiago, the spatio-temporal distribution of domestic violence against women shows clearly concentrated territorial patterns, with a greater concentration in the southwestern part of the city, which is related to lower income[2]. This distribution of domestic

[2] https://n9.cl/tugn

violence is related to the results of Gauvin *et al.* [22], who observe a larger gender gap in mobility patterns associated with the lower income areas of the city of Santiago.

Hypothesis

1. To the extent that women are victims of domestic violence - impacting their routines and lifestyles - it is expected that higher levels of violence will result in lower levels of mobility.
2. Associated with an agency approach, higher levels of female education and employment are expected to lead to greater female mobility.

Our results are evidence to validate the first hypothesis proposed. There is a negative and significant relationship between mobility and domestic violence against women, which would imply that female mobility would decrease in the presence of higher levels of domestic violence. This relationship is only observed in physical violence, being this type of violence the one that generates a strong decrease in female mobility (Pearson correlation of -0.78 with entropy and -0.87 with the number of trips). Regarding the agency approach, we do not observe evidence to validate our hypothesis. This relationship is not affected by factors such as education and female employment. Although both variables strongly correlate to female mobility, they do not explain it.

3.2 Data and Method

3.2.1 Data

Three sources of information were used. Police case records from the Center for the Study and Analysis of Crime (Undersecretary of Crime Prevention, Chile) were used to generate the indicators of domestic violence against women. These records correspond to complaints and arrests in flagrancy for domestic violence against women. Anonymized and aggregated mobile phone records from Telefónica Chile were used to measure and evaluate mobility. The third source corresponds to the Census of Population and Housing of Chile (INE, Chile), which has information on the resident population of the country at the block, zone, district and commune levels.

The unit of analysis was the commune. In Chile, the commune is the smallest administrative unit. There are 346 communes in the country, 52 of which are located in the Metropolitan Region of Chile. This region concentrates 40.5% of the population according to the 2017 Population and Housing Census. The research and analysis was conducted in the city of Santiago (Metropolitan Region), which is made up of 34 municipalities[3].

3.2.1.1 Domestic violence

We used records of domestic violence against women from 2017 in the urban area of the city of Santiago. Out of 20,750 geolocated records, 10,237 (49%) correspond to physi-

[3] Cerrillos, Cerro Navia, Conchalí, El Bosque, Estación Central, Huechuraba, Independencia, La Cisterna, La Florida, La Granja, La Pintana, La Reina, Las Condes, Lo Barnechea, Lo Espejo, Lo Prado, Macul, Maipú, Ñuñoa, Pedro Aguirre Cerda, Peñalolén, Providencia, Pudahuel, Puente Alto, Quilicura, Quinta Normal, Recoleta, Renca, San Bernardo, San Joaquín, San Miguel, San Ramón, Santiago y Vitacura.

cal domestic violence and 10,513 (51%) psychological violence. Only cases of violence against women that occurred in the victim's household were considered (about 5% of the cases occur elsewhere). Thus, we defined two indicators to evaluate domestic violence against women: physical and psychological violence. To compare results, we normalized the number of cases of domestic violence against women per 100,000 adult women in a territorial unit. To normalize, we used demographic information from the Chilean Population and Housing Census.

3.2.1.2 Mobility

Mobility was evaluated based on the indicators of Gauvin *et al.* [22], which was quantified from anonymized and aggregated mobile phone records from 2016, specifically for the months of May, June and July. This set of anonymized mobile phone records or CDRs contains information on gender, nationality, socioeconomic segment and number of telephone lines registered and associated with a certain telephone number. Starting from an identifiable location (home address) and with more than two different locations during three months, they worked with 418,624 unique users, 51% of whom were women. Two mobility metrics differentiated by gender, number of trips and entropy, were used [32, 22].

The number of trips corresponds to the number of locations or places a person has visited. When a cellular device interacts with the network there is a record of its connection to the antenna and the time it occurred. We consider as a trip the transit from one antenna to another. For two geographic territories, A and B, we have that the number of trips from A to B is estimated as the sum of the trips between antennas inside A and antennas inside B. It is important to note that these records do not give the exact location of the devices but rather the antenna to which it is connected.

Entropy, on the other hand, measures the diversity of individual mobility. This measure, measures Shannon's entropy of the trajectories of a user as:

$$S = -\sum_{l \in L} p_l \ln p_l \tag{3.1}$$

where L is all the locations visited by a user, and p_l is the probability of observing a user at location l, calculated as the fraction of calls made by the user at location l [22]. Accordingly, for a user with a high entropy it is concluded that they distribute their trips in many different locations with the same probability, while for a user with a lower entropy it would be concluded a higher regularity of their mobility patterns, in a smaller set of regularly visited locations [46, 32, 22].

3.2.1.3 Economic Independence

Freedom from domestic violence and female mobility, in an agency approach, could be related to women's economic independence. We define three indicators as proxies of economic independence or autonomy: female employment, occupational segregation and female education [12, 3, 18]. Female employment is defined as the percentage of women who are working out of the female population aged 15 years and older. Female labor force participation provides insight into how women contribute to economic growth and how they gain access to economic resources and improved well-being. Occupational segregation corresponds to a measure of the magnitude of the changes required in the employed population to achieve an equitable economic participation in occupations by gender [15]. Occupational segregation is useful to determine how much progress must be made in order to claim that there is gender equality in the participation of men and women in the labor market. Finally, female education corresponds to the average years of schooling of the female population aged 15 and older. Education would affect access to information and increase independence from their partner [19, 30, 11].

On the other hand, it was pointed out that negative partner attitudes and controlling behaviors would also be related to domestic violence against women. Given this, we defined an indicator for male education as the average years of schooling of the male population aged 15 years or older; and an indicator for male employment as the percentage of men who are working, with respect to the male population aged 15 years or older.

3.2.2 Method

The method considered a bivariate analysis, descriptive and inferential, to evaluate the relationship between variables. A t-test was used to compare means by type of violence, as well as characteristics by gender. The indicator used to evaluate the relationship between mobility and domestic violence was Pearson's linear correlation index.

The concept of confounding is probably one of the most important in causal relationships. The relationship between female mobility and domestic violence could be spurious (Figure 3.1) determined by a confounder. A confounder is a variable that is independently associated with both the exposure or explanatory variable and the outcome or explanatory variable. The path for a correct choice of this type of variables is called the "backdoor criterion" (Figure 3.2) which implies that the confounding factor Z blocks or intercepts every path between X and Y that contains an arrow towards X [40, 41, 48, 23]. Our hypothesis suggests that there would be a relationship between female mobility and variables related to economic independence (education and employment), but these variables would also affect violence against women, being these our confounding factor (Figure 3.3).

Figure 3.1: Causal Relationship.

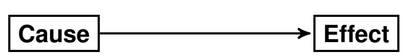


Figure 3.2: Backdoor Criterion.

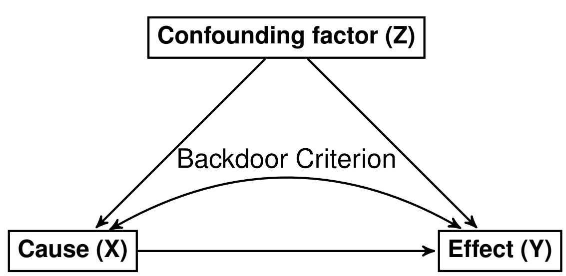
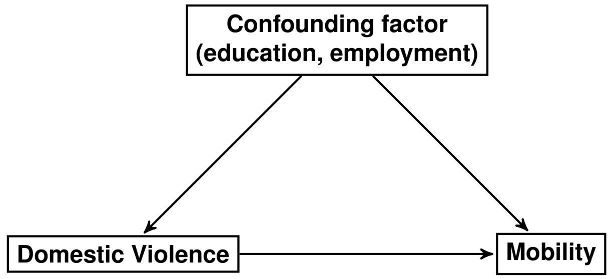


Figure 3.3: Backdoor criterion for the relationship between mobility and domestic violence against women.



The strategies used to control for confounding bias are multiple regression analysis and Propensity Score Matching (PSM).

In multiple regression, the confounder is included as an independent or explanatory variable. In this way, the directionality and magnitude of the association between the relevant variables before and after adjusting for the confounder is analyzed. For explanatory purposes and to evaluate causality, the functional relationship between female mobility and physical domestic violence was modeled. The technique used for the modeling was linear regression [26, 27]. In its simple linear form $Y = Movilidad$ and $X = Violencia$. Before evaluating the presence of a confounding factor in a multiple model, we tested for omitted variable bias with Ramsey's RESET test [43].

$$y_i = \beta_o + \beta_1 x_i + \varepsilon_i \tag{3.2}$$

$$Mobility_i = \beta_o + \beta_1 Violence_i + \varepsilon_i$$

$$y_i = \beta_o + \beta_1 x_{1i} + \beta_2 x_{2i} + \varepsilon_{ij} \tag{3.3}$$

$$Mobility_i = \beta_o + \beta_1 Violence_i + \beta_2 Confounding_i + \varepsilon_{ij}$$

Propensity Score Matching, based on a matching technique, has the advantage of controlling multiple confounding factors efficiently with fewer random errors. Experimentally, this is an advantage because this variable considers observations exposed and not exposed to a treatment, being the non-exposed, the group of observations that represent the counterfactual scenario, and from which a treatment or exposure can be evaluated in a result of interest. Matching is a method that consists of selecting and matching units seeking a homogeneous (1:1) distribution of experimental participants (one treated unit with one untreated unit), based on their probability of receiving the treatment or being exposed to a situation [44, 29, 28, 4]. This probability corresponds to the Propensity Score, and is estimated from the confounding factors. The pairs are selected by their similarity in the Propensity Score, evaluating in them the average effect of a treatment or exposure on a variable of interest.

In traditional matching methods, the exposure variables are dummies (treated or untreated), but in our case domestic violence, being the exposure variable, is continuous. Therefore, causal effects were estimated using a Generalized Propensity Score (GPS) estimated with Generalized Boosted Models (GBM) [31, 34, 52, 50]. Therefore, using

GPS we evaluated domestic violence against women as a continuous exposure variable, controlling for confounding factors, and from this, its effect on female mobility. GPS was estimated using the R package "twangContinuous"[4].

For each method and measure of mobility, five specifications were constructed where, in addition to domestic violence against women, variables related to economic independence are included, which could be generating a confounding bias. These factors are the variables: female education, female employment and occupational segregation. A first model considers female education; a second model considers female employment; a third model includes occupational segregation; a fourth model considers female education and female employment; and a fifth model includes female education and occupational segregation. It is important to note that we did not build a model based on female employment and occupational segregation because they are two highly correlated variables, with a Pearson's index of 0.93 ($p < 0.01$), which could generate collinearity between the two.

3.3 Results

3.3.1 Description of Variables

Female entropy and number of trips present a mean of 1.67 and 28.94, respectively. For physical domestic violence, the mean is 552.7, while the mean for psychological violence is 515 (both correspond to police cases per 100,000 women). Both means do not show significant differences according to the t-test.

With respect to education, we observe an average of 14.08 and 15.07 years of schooling for women and men, respectively. There are no significant differences between years of schooling by gender. In the case of employment, 74% of men report having a job, compared to 58% of women who do. In employment, significant differences are observed between men and women ($p < 0.01$). Occupational segregation has a mean of -0.08, which implies an average occupational segregation to the detriment of women (positive values imply occupational segregation in favor of women and negative values in favor of men).

3.3.2 Relationship between variables

When relating mobility with violence, only physical violence presents a significant relationship ($p < 0.01$) with female mobility, with a Pearson's index of -0.78 with entropy and -0.87 in the number of trips (Table 3.1). The relationship with entropy implies that the greater the number of visits, in many different places, the less physical violence women suffer. Likewise, the number of trips implies that as more women travel (the number of trips increases) the physical domestic violence of which they are victims decreases. Although psychological violence has a significant relationship with female travel ($p < 0.05$), the association between the two variables is low (-0.38).

[4]https://cran.r-project.org/web/packages/twangContinuous/vignettes/briefTutorial.html

Table 3.1: Pearson's correlation between domestic violence and mobility.

	Physical	Psychological
Entropy	-0.78	-0.30^b
Trips	-0.87	-0.38^a

All values are statistically significant at $p < 0.01$, except x^a $p < 0.05$, and non-statistically significant, marked as x^b.

Table 3.2 presents the correlations between domestic violence against women and female mobility with respect to education, employment and occupational segregation. With the exception of male employment, all variables have a significant relationship with domestic violence against women and their mobility ($p < 0.01$).

Table 3.2: Pearson's correlation between domestic violence/mobility and educational and labor variables.

	Physical violence	Psychological violence	Entropy	Trips
Male education	-0.88	-0.59	0.72	0.80
Female education	-0.86	-0.60	0.69	0.75
Male employment	-0.11^b	-0.01^b	-0.00^b	-0.18^b
Female employment	-0.71	-0.53	0.67	0.62
Occupational segregation	0.85	0.61	-0.77	-0.79

All values are statistically significant at $p < 0.01$, except x^a $p < 0.05$, and non-statistically significant, marked as x^b.

Physical violence shows a significant relationship with education, presenting a correlation of -0.88 and -0.86 with respect to male and female education, respectively. This association is higher that observed with psychological violence, which is related to -0.59 with male education and -0.60 with female education. These relationships imply that domestic violence against women would be lower with higher levels of schooling in the population. Female employment is negatively associated with physical domestic violence, presenting a correlation of -0.71; with psychological violence, although a significant relationship is observed, it presents a low association (-0.53). Therefore, domestic violence against women would decrease with higher female employment rates. Occupational segregation also shows a strong association with domestic violence, with a correlation of 0.85 for physical violence and 0.61 for psychological violence. This implies that a greater labor gap against women would be associated with higher levels of domestic violence against them, mainly physical violence.

When evaluating entropy, a positive relationship with education is observed, with a correlation of 0.72 for male education and 0.69 for female education. This implies that female entropy increases when the education of the population increases. With female employment, entropy is positively associated (0.67), which is evidence of greater mobility with greater female labor participation. The relationship with occupational segregation presents a correlation of -0.77, which implies that the greater the occupational segregation, that is, when there is greater labor inequality in favor of men, the lower the female entropy.

Regarding the number of trips, there is a correlation of 0.80 with male education and 0.75 with female education. These relationships imply that the number of female trips increases with a higher educational level of the population. Female employment shows a positive relationship and a correlation of 0.62, which implies that female mobility increases with female employment. The relationship with occupational segregation is negative, with a correlation of -0.79, which implies that the number of female trips is higher when there is less occupational segregation against women.

3.3.3 Modeling

When relating domestic violence against women to their mobility, we only found a significant relationship for physical violence (Table 3.1). Therefore, the causal evaluation was only performed for this type of violence.

A simple model shows a significant dependence relationship (Table 3.3). This would imply that female mobility would depend on physical violence against women ($p < 0.01$).

Table 3.3: Linear models (dependent variable: physical domestic violence, independent variable: mobility).

	Entropy	Trips
Intercept	1.8601^a	35.6420^a
	(0.0292)	(0.7143)
Domestic violence	-0.0004^a	-0.0121^a
	(0.0000)	(0.0012)
R-squared	0.6105	0.7569
R-squared Adj.	0.5983	0.7493
N	34	34

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

However, we evaluated whether these models have omitted variables, which could be the confounding factors mentioned above. The Ramsey test posits the absence of omitted variables as the null hypothesis, i.e., that the model would be well specified, with respect to an alternative hypothesis that variables have been omitted in the model. In Table 3.4 we observe statistical evidence ($p < 0.01$) that there are no omitted variables to explain female entropy and number of trips as a function of physical domestic violence.

Table 3.4: Ramsey's RESET test for omitted variables.

	F-stats	p-value
Entropy	0.652	0.588
Trips	0.656	0.585

As we have analyzed, the strategies to control for the confounding bias are the multiple regression analysis and the Matching technique. According to the Ramsey test, it would not be necessary to evaluate a model that incorporates variables related to economic independence to explain female mobility. However, we evaluated these variables to validate this test and its result.

The following are the multiple linear models that incorporate female education, female employment and occupational segregation. Table 3.5 presents the models to account for female entropy. In the first four specifications, the only significant variable with a negative parameter is domestic violence ($p < 0.01$). Model 5 presents significant and negative parameters for domestic violence ($p < 0.01$) and occupational segregation ($p < 0.05$). Although the female education and employment variables, as well as occupational segregation, show significant correlations with female entropy (Table 3.2), these variables do not explain mobility, which implies that female entropy would only decrease with higher rates of domestic violence, except in model 5 where occupational segregation would imply a gender labor gap and therefore also lower female mobility.

Table 3.5: Linear models (dependent variable: physical domestic violence, independent variable: entropy).

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.7852^a	1.5942^a	1.8848^a	1.8941^a	2.4317^a
	(0.3051)	(0.1687)	(0.0308)	(0.2962)	(0.3927)
Domestic violence	-0.0003^a	-0.0003^a	-0.0002^b	-0.0004^a	-0.0003^b
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Female education	0.0043			-0.0285	-0.0303
	(0.0173)			(0.0232)	(0.0217)
Female employment		0.3827		0.6700	
		(0.2393)		(0.3334)	
Occupational segregation			1.4167		2.3249^b
			(0.7360)		(0.9738)
R-squared	0.6113	0.6402	0.6521	0.6574	0.6733
R-squared Adj.	0.5862	0.6170	0.6296	0.6231	0.6407
N	34	34	34	34	34
	34	34	34	34	34

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Table 3.6 presents the models to explain the number of trips. In the five specifications, the only significant and negative variable is domestic violence ($p < 0.01$).

As with female entropy, although variables for female education, female employment and occupational segregation show significant correlations with female travel (Table 3.2), these variables do not explain this measure of mobility, which would imply that the number of female trips would be lower only when levels of physical domestic violence against women increase.

Table 3.6: Linear models (dependent variable: physical domestic violence, independent variable: number of trips).

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	34.7498^a	35.0685^a	35.9671^a	34.8500^a	43.3223^a
	(7.4781)	(4.2967)	(0.7862)	(7.7316)	(10.2498)
Domestic violence	-0.0119^a	-0.0119^a	-0.0101^a	-0.0119^a	-0.0108^a
	(0.0024)	(0.0017)	(0.0023)	(0.0025)	(0.0025)
Female education	0.0509			0.0208	-0.4076
	(0.4248)			(0.6065)	(0.5664)
Female employment		0.8254		0.6162	
		(6.0953)		(8.7023)	
Occupational segregation			18.6096		30.8245
			(18.7756)		(25.4187)
R-squared	0.7570	0.7570	0.7644	0.7571	0.7684
R-squared Adj.	0.7413	0.7414	0.7492	0.7328	0.7452
N	34	34	34	34	34

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

The results with the Matching technique (GPS) are presented in Table 3.7 for entropy and in Table 3.8 for number of trips. For each mobility measure, the same five specifications are presented. The results show a dependence relationship between mobility and physical domestic violence, controlled by female education and employment, as well as by occupational segregation. Both, entropy and number of trips, present significant parameters ($p < 0.01$). This would imply that, given the control for possible confounding factors related to economic independence, female mobility would present a causal relationship with violence, decreasing in the face of higher rates of physical domestic violence.

Table 3.7: Matching estimates (dependent variable: entropy, independent variable: physical domestic violence).

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	1.8659^a	1.8580^a	1.7960^a	1.8630^a	1.8470^a
	(0.0247)	(0.0341)	(0.0255)	(0.0249)	(0.0281)
Domestic violence	-0.0004^a	-0.0003^a	-0.0002^a	-0.0003^a	-0.0003^a
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

Table 3.8: Matching estimates (dependent variable: trips, independent variable: physical domestic violence).

	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	35.2250^a	35.9267^a	34.0335^a	35.2270^a	34.6722^a
	(0.7082)	(1.2335)	(0.7975)	(0.7260)	(0.7429)
Domestic violence	-0.0108^a	-0.0118^a	-0.0082^a	-0.0111^a	-0.0104^a
	(0.0013)	(0.0020)	(0.0013)	(0.0012)	(0.0014)

Standard errors in parentheses, x^a parameters statistically significant $p < 0.01$ and x^b statistically significant at $p < 0.05$.

The supplementary material presents the results of these estimations performed with

Bootstraping. For each method, when comparing the interval estimates with and without Bootstrapping, no differences in the parameters and their statistical significance are observed, this being a robustness measure to validate our results.

3.4 Discussion and Conclusions

A negative relationship is observed between female mobility and domestic violence against women. This relationship is significant and stronger with physical violence. This implies that the higher the prevalence of being a victim of physical domestic violence, the lower female mobility.

The multivariate and matched models constructed show a causal relationship between female mobility and physical domestic violence. Therefore, we can conclude that female mobility decreases as physical violence against women increases. This relationship would not be related to agency factors related to economic independence, such as education and female employment, but in the case of entropy, it would be a gender labor gap generated by occupational segregation.

The absence of a relationship between psychological domestic violence and mobility could indicate that this type of violence is more transversal and female mobility would not be affected when they are victims of this type of violence. It is important to carefully observe this relationship, since psychological violence in Chile has a higher rate of unreported cases. A significant number of cases do not appear in official records. According to the National Survey of Domestic Violence against Women of the Center for Crime Studies and Analysis (CEAD, Chile), only 22.8% of cases of psychological violence were reported in 2017, while only 19% were reported in 2020. This could be due to a lack of knowledge of what it is or the type of aggression involved in psychological violence against women. On the other hand, physical domestic violence is accompanied by psychological violence, with physical violence being that which is denounced by women or that which is identified in the report issued by the authorities.

Economic autonomy contributes to gender equality, being a protective factor regarding violence against women. Women's employment and education are related to their mobility [1], and therefore to gender violence. The literature indicates that female employment may not be related to violence against women, as there is no consensus on how it affects it [30, 11, 49]. Our results show that female employment - although significantly related to female mobility and domestic violence against women - does not explain their mobility. Regarding female education, there is also no consensus on its effect on domestic violence [51, 20, 2, 49]. Although our results show a significant relationship between female education with mobility and violence, it is not a causal relationship. Therefore, we have no evidence that female employment and education are protective against domestic violence against women.

A negative and significant relationship, with a high association, is observed between female mobility and occupational segregation. This labor gap would not explain women's mobility. This relationship is relevant because female labor participation and mobility allows us to know how women contribute to economic growth and how they access economic resources and better welfare.

Regarding negative partner attitudes and controlling behaviors toward female mobility and employment, our results show that male education is positively related to female mobility and negatively related to physical domestic violence. This implies that higher male education translates into lower levels of violence against women and greater mobility. This result validates the view that male education affects access to information and increases women's independence [19, 30, 11]. On the other hand, we did not observe a relationship between male employment and female mobility and domestic violence against women, so we have no evidence that their independence is conditioned by the employment situation of men [11].

The literature has not yet characterized urban mobility with a gender focus in depth. A first study that characterizes mobility in the city of Santiago concludes differences between men and women in relation to the places that both visit regularly [22]. Similarly, the territorial distribution of domestic violence against women in the city of Santiago shows patterns of concentration[5] that are related to low mobility. Therefore, it is necessary to study these phenomena and characterize them with a gender approach, since mobility is a measure that captures the dynamics of people's behavior, and violence against women is not foreign to this relationship.

It is necessary to continue to evaluate and determine what other variables contribute to explaining domestic violence against women and its consequences. Assessing the relationship between crime and mobility is not new. Our contribution is to give a new use to mobility measures estimated from digital traces of mobile devices, evaluating them and relating them to a crime committed against women: domestic violence. This evidence would allow decision makers to design public policies and target interventions that reduce or eliminate this phenomenon.

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3.5 Supplementary Material

3.5.1 Descriptive statistics

Table 3.9: Descriptive statistics of female mobility.

	Female entropy	Female trips
Count	34.00	34.00
Mean	1.67	28.94
Standard deviation	0.09	2.83
Minimum	1.50	24.46
P(25)	1.60	26.52
P(50)	1.67	28.76
P(75)	1.73	30.33
Maximum	1.84	35.16

Figure 3.4: Distribution of female mobility.

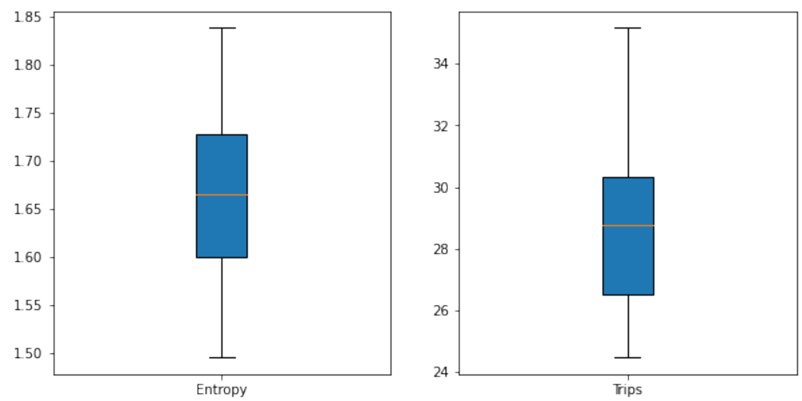

Table 3.10: Descriptive statistics of domestic violence against women.

	Physical	Psychological
Count	34.0	34.0
Mean	553.7	515.0
Standard deviation	203.6	175.0
Minimum	101.5	185.3
P(25)	475.3	385.5
P(50)	596.5	479.2
P(75)	715.0	644.9
Maximum	821.8	836.1

Figure 3.5: Distribution of domestic violence against women.

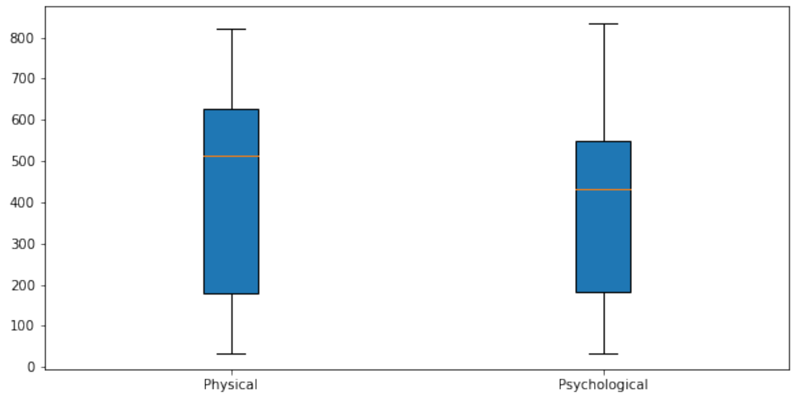

Table 3.11: Descriptive statistics of educational and labor variables.

	Male education	Female education	Male employment	Female employment	Occupational segregation
Count	34.00	34.00	34.00	34.00	34.00
Mean	15.07	14.80	0.74	0.58	-0.08
Standard deviation	1.26	1.16	0.02	0.06	0.03
Minimum	12.95	12.83	0.70	0.49	-0.11
P(25)	14.20	14.09	0.72	0.54	-0.10
P(50)	14.73	14.55	0.73	0.57	-0.08
P(75)	15.64	15.34	0.75	0.62	-0.06
Maximum	18.06	17.66	0.79	0.72	-0.03

3.5.2 Model Robustness

Since we are working with aggregated information at a commune level, and our population corresponds to the 34 communes that make up the city of Santiago, we validated our results with Bradley Efron's Bootstrapping method [17]. This technique allows us to model and make inferences from a resampling of the sample data and make an inference on these new samples. For each model, 10,000 simulations or resampling with replacement were performed. For each method and estimate, 95% confidence intervals are presented. Table 3.12 and Table 3.13 present the multivariate estimates to explain the entropy and the number of trips, respectively. Table 3.14 and Table 3.15 show the Matching (GPS) estimates to explain entropy and number of trips, respectively.

Table 3.12: 95% confidence intervals for multivariate bootstrapped estimation parameters (dependent variable: entropy, independent variable: physical domestic violence).

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
OLS	Intercept	1.1628	2.4075	1.2501	1.9382	1.8220	1.9477	1.2892	2.4990	1.6298	3.2337
	Domestic violence	-0.0005	-0.0001	-0.0004	-0.0001	-0.0004	-0.0000	-0.0006	-0.0002	-0.0005	-0.0001
	Female education	-0.0311	0.0396					0.0760	0.0189	-0.0746	0.0149
	Female employment			-0.1053	0.8708			-0.0108	1.3509		
	Occupational segregation					-0.0844	2.9178			0.3361	4.3137
OLS with Bootstraping	Intercept	1.3200	2.3023	1.2828	1.8915	1.8420	1.9453	1.4165	2.4728	1.7071	3.3950
	domestic violence	-0.0005	-0.0002	-0.0004	-0.0002	-0.0003	-0.0000	-0.0005	-0.0002	-0.0004	-0.0001
	Female education	-0.0247	0.0311					-0.0787	0.0120	-0.0831	0.0100
	Female employment			-0.0367	0.8254			0.0122	1.3226		
	Occupational segregation					0.4085	2.8084			0.5833	4.4930

Table 3.13: 95% confidence intervals for bootstrapped multivariate estimation parameters (dependent variable: number of trips, independent variable: physical domestic violence).

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
OLS	Intercept	19.4981	50.0016	26.3052	43.8317	34.3636	37.5707	19.0599	50.6401	22.3894	64.2551
	Domestic violence	-0.0168	-0.0069	-0.0155	-0.0084	-0.0149	-0.0054	-0.0170	-0.0068	-0.0160	-0.0056
	Female education	-0.8155	0.9174					-1.2178	1.2594	-1.5643	0.7490
	Female employment			-11.6061	13.2569			-17.1563	18.3886		
	Occupational segregation					-19.6835	56.9027			-21.0874	82.7365
OLS with Bootstraping	Intercept	22.2138	50.1450	27.1725	42.9158	34.5306	37.7107	22.0145	52.1184	22.1969	69.8135
	Domestic violence	-0.0168	-0.0077	-0.0154	-0.0083	-0.0138	-0.0055	-0.0171	-0.0076	-0.0154	-0.0061
	Female education	-0.8092	0.7786					-1.3641	1.1243	-1.8873	0.7732
	Female employment			-9.8832	11.7899			-16.7645	17.3382		
	Occupational segregation					-5.3409	55.4507			-14.7014	87.2462

Table 3.14: 95% confidence intervals for bootstrapped matching estimation parameters (dependent variable: entropy, independent variable: physical domestic violence).

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
OLS	Intercept	1.8156	1.9162	1.7884	1.9274	1.7497	1.8482	1.8126	1.9138	1.7900	1.9044
	Domestic violence	-0.0004	-0.0002	-0.0004	-0.0002	-0.0003	-0.0001	-0.0004	-0.0003	-0.0004	-0.0002
OLS with Bootstraping	Intercept	1.7825	1.8887	1.7872	1.9531	1.8282	1.8850	1.7441	1.8760	1.8489	1.9852
	Domestic violence	-0.0004	-0.0002	-0.0005	-0.0002	-0.0004	-0.0003	-0.0004	-0.0001	-0.0006	-0.0003

Table 3.15: 95% confidence intervals for bootstrapped matching estimation parameters (dependent variable: number of trips, independent variable: physical domestic violence).

		Model 1		Model 2		Model 3		Model 4		Model 5	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
OLS	Intercept	33.7824	36.6676	33.4142	38.4393	32.4090	35.6579	33.7488	36.7052	33.1589	36.1853
	Domestic violence	-0.0134	-0.0082	-0.0158	-0.0077	-0.0107	-0.0057	-0.0136	-0.0086	-0.0132	-0.0076
OLS with Bootstraping	Intercept	33.1239	36.1606	32.6804	38.2781	33.7865	35.4687	32.7708	36.3353	34.3513	36.4897
	Domestic violence	-0.0126	-0.0079	-0.0161	-0.0068	-0.0126	-0.0093	-0.0130	-0.0061	-0.0148	-0.0107