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CAF DEVELOPMENT BANK OF LATIN AMERICA

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ABSTRACT

This paper explores the relationship between urban public transportation innovation and crime. In 2004, the city of Medellin in Colombia developed an innovative public transportation system based on cable cars (Metrocable) to reach dense, isolated and dangerous neighborhoods. Using Spatial Difference in Difference approaches and a rich dataset at spatial analytical level, using max-p modeling, we explore the effects of the Metrocable on crime and its mechanisms. We find a significant impact on homicides reduction in the treated neighborhoods, especially in the medium run. Homicides decreased around 41% more than the general crime reduction in the city between 2004 and 2006, and by 49% between 2004 and 2012. We explore two mechanisms through which this intervention may affect the level of criminality, one is reducing the travel costs and improving accessibility to the rest of the city for low-income population (socioeconomic mechanism); the other is the increasing of the probability of apprehension for potential and active o enders (deterrent mechanism).

WORKING PAPERS

MOVILIZANDO CIUDADANOS Y DISUADIENDO CRIMINALES: INNOVACIÓN EN INFRAESTRUCTURA DE TRANSPORTE PÚBLICO

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RESUMEN

Este artículo explora la relación entre la innovación en transporte público urbano y el crimen. La inversión en transporte público puede afectar los patrones criminales dependiendo del diseño de la intervención. En 2004, la ciudad de Medellín en Colombia desarrolló un sistema de transporte público innovador basado en teleféricos (Metrocable) para alcanzar barrios densos, aislados y peligrosos. Usando una metodología de Diferencias en Diferencias Espacial y una base de datos rica en información a nivel de barrios, exploramos los efectos del Metrocable sobre el crimen. Encontramos un impacto significativo de la intervención sobre la reducción de homicidios en los barrios tratados. Los homicidios decayeron alrededor de un 10% adicional sobre la reducción general del crimen en la ciudad entre 2003 y 2006. También identificamos dos mecanismos a través de los cuales esta intervención afectó el nivel de homicidios, uno es la reducción de los costos de transporte y la mejora de la accesibilidad al resto de la ciudad para la población de bajos recursos (mecanismo socioeconómico); el otro es el aumento en la probabilidad de captura para criminales potenciales o activos (mecanismo de disuasión).

Moving Citizens and Deterring Criminals: Innovation in Public Transport Facilities*

By Gustavo Canavire-Bacarreza[†] Juan Carlos Duque[‡]
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This paper explores the relationship between urban public transportation innovation and crime. In 2004, the city of Medellin in Colombia developed an innovative public transportation system based on cable cars (Metrocable) to reach dense, isolated and dangerous neighborhoods. Using Spatial Difference in Difference approaches and a rich dataset at spatial analytical level, using max-p modeling, we explore the effects of the Metrocable on crime and its mechanisms. We find a significant impact on homicides reduction in the treated neighborhoods, especially in the medium run. Homicides decreased around 41% more than the general crime reduction in the city between 2004 and 2006, and by 49% between 2004 and 2012. We explore two mechanisms through which this intervention may affect the level of criminality, one is reducing the travel costs and improving accessibility to the rest of the city for low-income population (socioeconomic mechanism); the other is the increasing of the probability of apprehension for potential and active offenders (deterrent mechanism).

JEL: C33, H54, H76, O18, R1, R42, R48

Keywords: spatial, impact evaluation, public transport, Medellin, public investment

I. Introduction

Over the last two decades, population and economic growth (especially in urban areas) have increased the need for expanding and improving infrastructure efficiency as a way to integrate people into society and increase mobility across and within cities (Munnell, 1992; Sanchez-Robles, 1998; Holtz-Eakin and Schwartz,

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1995). Investment on infrastructure has been one of the main public policy instruments to promote economic and human development in search for equality, and as a way to reduce crime through different channels such as the social inclusion and the reduction of payoffs of crime in urban areas (Glaeser and Sacerdote, 1999; La Vigne, 1996; Cozens et al., 2003; Crowe, 2000).

The city of Medellin (Colombia), with a population of 2.4 million, presents a unique framework to study the relationship between public infrastructure and crime. Two decades ago Medellin was considered one of the most unequal and violent cities in the world (Giraldo Ramírez, 2010). However, the city showed a remarkable reduction in crime rates, with an average annual homicide rate dropping from 380 homicides per 100,000 inhabitants in the early 1990s, to 98.2 in 2003 and 26.95 in 2014. After important military operations such as the end of the Medellin drug cartel in 1993 and the Orion operation to retake control over the western part of the city in 2002, local authorities implemented other innovative, non-military, initiatives to deal with the problems that arise when a fast growth city exceeds the capacity of the local authorities to deliver services and infrastructure (Ibáñez and Vélez, 2008; Patiño et al., 2014). These initiatives sought to impact mobility, integration and crime simultaneously. One of the most important investments during this period was the construction of the cable car (*Metrocable*) in 2014, which connected the most deprived and far-flung neighborhoods located in the north-eastern hills of the city (with slopes steeper than 20%) to the Medellin Metro System. The Metrocable reduced commuting time from 2.5 hours to seven minutes (United Nations, 2007).

Although several authors have studied the impact of the Metrocable on the socioeconomic conditions of the north-eastern neighborhood of Medellin (Bocarejo et al., 2014; Cerda et al., 2012), from the best of our knowledge, no study has attempt to quantify the mechanisms through which the Metrocable affects homicide rates. Furthermore, no previous study have considered the spatial nature of such intervention, which implies that the presence of a new transport infrastructure not only affects the neighbouring areas but also, via spillovers or indirect spatial effects, can affect further areas.

This paper aims to identify the effects of the construction of the Metrocable on homicide rates. We argue that there may be at least two main mechanisms through which this public infrastructure affects homicide rates. First, a socioeconomic mechanism through which this new public transportation system increases people's accessibility to more opportunities and amenities, which can play an important role in reducing criminal activities in the area. This mechanism is related to the spatial-mismatch theory, first proposed by Kain (1968), which states that opportunities for low-income people are inaccessible from where they live.[1]

[1] Some additional evidence is provided by Gilderbloom and Rosentraub (1990), who found that areas with low income and where disabled people live in Houston are less integrated into public transportation and present greater rates of fear of crime and victimization. Also, Crowe (2000) exposed the link between city infrastructure design and crime prevention, indicating the relationship between fear of crime, victimization, and quality of life.

Second, a deterrent mechanism through which the presence of a new public infrastructure usually increases the level of surveillance, and therefore increases the probability of apprehension, serving as a deterrent for potential offenders (Becker, 1968). This mechanism is also related to the routine activities theory, first proposed by Cohen and Felson (1979), which states that criminal acts require convergence in space and time of an offender, a target, and the absence of surveillance against crime.

This paper contributes to the current literature in two ways. First, we propose a way to estimate treatment impacts and their mechanism when the treatment is particularly related to a geographical intervention. To do this we extend the literature of spatial treatment effects to include a method to examine mechanisms in spatial difference in difference models. Based on these methods, a second contribution is a precise estimation of the effects of infrastructure on crime.

The remainder of this paper is organized as follows. The second section presents a literature review focused on the link between infrastructure investment and crime reduction. The third section presents the methodology used and the identification of the problem. The fourth section describes the datasets used, and the next section offers our results. Finally, the sixth section provides a conclusion to this analysis.

II. Literature Review

The study of the relationship between crime and place goes back to middle of the 19th-century, when social ecologists Guerry and Quetelet explored how the variation in the social conditions of the resident populations causes differences in community crime levels (Anselin et al., 2000). Later, in the early 20th century, the social disorganization theory, developed by the Chicago School, studied the aspects of crime that come from outside of a person and linked crime rates to neighborhood ecological characteristics. According to this theory, unfavorable neighborhood conditions such as poverty and unemployment, results into high crime rates (Shaw and McKay, 1942). It was until the end of the 20th century, with the appearance of the place-based theories of crime such as the routine activities theory (Cohen and Felson, 1979), that the research focus moved towards the study of the mechanisms by which the structural organization of places affects individual action.

According to the routine activities theory, criminal acts require convergence in space and time of an offender, a target, and the absence of surveillance against crime. In this contexts, there exist two ways in which the transformation of a place due to a new public transportation infrastructure can affect crime rates. The first one argues that since public transportation (bus, train, and metro) tends to concentrate a considerable number of people into specific places, potential delinquents have the incentive to move into these areas and commit crimes. In contrast, the other theory claims that the investment in public transportation allows the creation of what are perceived to be security-zones or places that perceived as safe areas even if those places fall within areas not considered secure.

Based on these two possibilities Brantingham and Brantingham (1995) state that cities' areas can be labeled based on their effects on crime. Some places are *crime generators*, which means that these places tend to be located where people are concentrated for reasons not related to crime (e.g. amusement parks, shopping centers, malls, etc.); while other places can be considered *crime attractors*, where potential delinquents are attracted to go given the number of opportunities to commit a specific kind of crime (e.g. red light districts and drug markets). Those areas *crime-neutral* are places where crime happens without a specific pattern and *fear generators*, places where citizens are afraid to go given their particular characteristics (isolation, low police control, etc.).

Brantingham and Brantingham (1995) argue that public transportation stations are places with non-unique characteristics and their taxonomy is directly related to the public planning, geographical location, and community perceptions. Public transportation stations, thus, might be labeled as crime generators, crime attractors, or fear generators. This leads us to the conclusion that there is not a specific role of the public transport facilities, that indeed their environment can be manipulated to obtain different outcomes.

Newton (2004) and Block and Davis (1996) focused their analysis on public transportation criminality using a particular distinction between the measurement of static and non-static criminal events. In his research, not only Newton has exposed the relevance of public transportation as a crime attractor and crime generator, but he has also presented a complex scenario in which crime and transportation interacts (vehicles, stations, and users). Such interactions establish the environment of public transportation and the challenges that surround planning public policy.

In addition, Loukaitou-Sideris et al. (2001, 2002) used information about the green line of Los Angeles metro to identify the effect of public transportation on crime. Loukaitou-Sideris et al. (2001, 2002) results demonstrated that there is no strong evidence of a direct positive effect on all metro stations on crime. Some stations, however, are more strongly interlinked with crime patterns in certain neighborhoods and the frequency of acts of delinquency inside the transportation system. The authors also suggested that effects on crime depend on the characteristics of the stations, which are strongly related to the characteristics of the neighborhoods in which the stations are located. The previous research studies with these authors (Levine and Wachs, 1986; Brantingham and Brantingham, 1993; Loukaitou-Sideris, 1999) have established the validity of the first theory mentioned above, in which public transportation stations play the role of an attractor of crime given their particular tendency to concentrate citizens in one area.

The way that these articles studied the relationship between transportation and crime depends on the particular location-specific characteristics of the area that was studied, which raises other questions. Should the public transportation offerings or their facilities be designed according to the environment in order to preserve or to transform them? Both options have advantages and disadvantages: designing to preserve allows citizens to feel more comfortable and adapt more quickly to new systems, but creating the systems with the same characteristics of the area in which they are located clearly cannot be the best option.

Other authors have focused on the improvements in public transportation and the entire system not as criminal hotspots, but as communities places that generate improvements in crime perception. Cozens et al. (2003) analyzed the crime perception of train stations and their infrastructure improvements in South Wales, United Kingdom. In their study, the authors proposed some improvements, such as better lighting, cameras, and cutting back the surrounding vegetation. All of these scenarios contribute to an improvement in crime perception and can possibly decrease crime rates.

A study of neighborhoods in Perth, Australia, developed by Foster et al. (2010) found the completely opposite relationship between fear of crime and proximity to public transportation stations. The authors, however, provide an explanation for the mechanism through which living closer to a public transportation station reduces the fear of crime. The mechanism exposed in Foster et al.'s paper is based on previous research (Jacobs, 1961; Cozens, 2008) in which neighbors play an important role. Citizens feel safer if they believe that others are monitoring their actions and will provide help in the event criminal activity occurs.

La Vigne (1996) presented a research study about the effects of the design, management, and maintenance of the Washington D.C. metro system on city crime. The author argued that this case can be cataloged as one of the most successful interventions. According to this research, the metro system has been able to maintain low crime rates both inside the system and within the area where the facilities are located. La Vigne finally argues the following: "Metro's success suggests that it is indeed possible to manipulate environments to reduce criminal opportunities. Further, it implies that offenders do consider the costs and benefits of their actions, weighing the risks of apprehension versus the effort and expected payoff, and considering the presence of capable guardians when weighing those risks". (p. 191).

A related study for the case of Medellin was developed by Cerda et al. (2012), who also examines the effect of Metrocable on crime. Cerda et al. (2012)'s paper designed a survey after the Metrocable was built based on previous survey made in the city and found that the homicide rate in neighborhoods where the new public transportation was developed decreased 66% more than in the control neighborhoods. Although the results of Cerda et al. (2012) are encouraging in terms of urban public infrastructure the study had some limitations, which can bias the total treatment effects on targeted neighborhoods. The lack of information at a low geographical level is only one of the reasons for possible misidentification. Control neighborhoods should have been selected from all the neighborhoods in the city. The randomized process would have been more efficient if the covariates had been related to political and socioeconomic characteristics rather than community perception variables.

Despite the fact that another work has already addressed the link between public transportation and crime rates, we believe it is important to further address this relationship. First, we should clarify that the results for Cerda et al. (2012) focused on the greater crime reduction of treated units over some control neighborhoods; our analysis broadly examines this effect in regard to the greater crime reduction of treated units over crime patterns of the rest of the neighborhoods in the city. Second, our data allows us to drive a short term analysis and medium run estimations, which include socioeconomic controls to better identify the impact. Also some robustness checks can be done using month variation panel structure to determine the specific moment of time when the metrocable intervention starts to impact crime outcomes.

Another important difference is given by the methodology used; our study uses a spatial impact design that broke the impact of treatment into two components, the direct impact of treatment on treated units (referring to those neighborhoods where the facilities are located) and the indirect impact of treatment on non-treated units that are close geographically to the treated units (which we called the spatial impact of treatment, referring to the neighbors of the treated neighborhoods). This decomposition is important to identify the areas where the intervention had some impact and to corroborate whether there is evidence of crime displacement. For our study, we are not going to control for perception variables. Instead, we will use socioeconomic variables. Although we do not include in our randomized process perception variables, which can raise some particular difficulties (e.g., people usually identified higher improvements in crime perception when they have lived in a high violence area than if they have lived in lower violence areas), we will not be able to discern any relationship between homicides and the treatment driven by improvements in variables such as feeling safe, fear or crime, sense of victimization, etc.; we only can identify the impact of the treatment on the outcome. The Cerda et al. study has a much better design in this strategy and also covers another bunch of crime outcomes. One of the socioeconomic problems that this research wants to discuss is the effectiveness of public transportation investments as a public security-oriented policy. It is important to note that all public policy design should take into account the indirect effects caused by policy interventions. Those indirect effects can be in the form of a positive externality, like the Metro success for Washington La Vigne (1996) and the Metrocable success for Medellin, but the indirect effects can also behave as negative externalities, as described for Los Angeles and Chicago (Loukaitou-Sideris et al., 2001, 2002; Block and Davis, 1996). A misunderstanding of this link can lead to some undesirable results depending on the examined city. The case study of Medellin is fundamental to the analysis of the determinant factors that interact between public security and crime, how these interventions work, and the capacity of these interventions to improve criminal outcomes in an urban framework. The relationship between the level of crime and metro systems is an important issue for cities, and Medellin is one example of how public transportation can affect crime. Furthermore, the specific case of Medellin can help other cities achieve better results in their objective to reduce crime. Cities located in Central America, especially in Mexico, where their cities have been facing a considerable increase in violence compare to their levels prior 2005 due mainly to the fight of drug cartels and organized crime; similar to that faced in the 90's and beginning of 2000's by Medellin. Also, the most populated cities in El Salvador, Honduras and Brazil can really benefit of this analysis, since most of them are working on better public transport models and also face high rates of crime.

III. Methodology

A. Treatment and Outcome, Mechanism of Interaction

We depart from the hypothesis that the Metrocable public system led to a greater reduction of homicides between 2004, 2006 and 2012 in the area in which it is located. Thus, the new facilities could be viewed as security zones for the resident population and as mechanisms to improve their access to the rest of the city while at the same time reducing travel costs. In fact, improvements in the accessibility and the travel cost reduction could affect homicides through different factors. Yet, two of the most important are labor markets and apprehensions. We argue that the implementation of the Metrocable had an "inclusive" effect since it created better opportunities for people that would otherwise be isolated. People living in the suburbs are now able to access the main city markets, which has an effect on unemployment, informality, and wages (see, for example, Menezes et al. 2013; Scorzafave and Soares 2009; Lochner 1999).

The spatial-mismatch hypothesis is particularly related to this mechanism. Kain (1968) argues that differences in employment rates inside cities are link to some segregation across the city, evidencing a correlation between where people live and their possibilities to find a job. Recent studies corroborate this theory, stating that in the USA those who take longer to find a job are characterized by high levels of segregation and are far away from the jobs opportunities, or they come from neighborhoods that the employer thinks are "bad". This theory is relevant for our mechanism because it shows that isolated population is particularly vulnerable to unemployment and informality, and the situation worsens if there is not good public transportation system. Gobillon and Selod (2007), Patacchini and Zenou (2005) and Andersson et al. (2014) found similar results.

A second mechanism through which this investment led to crime reduction is the increased probability of apprehension. The Metrocable stations are places where police presence is constant, and the stations have security cameras that monitor any event taking place in the surrounding areas or within the system. So when an offender commits a crime in close proximity to any station, the probability of getting caught for committing that crime increases. This new form of public transportation, then, works to deter potential criminal activity and tends to shift the location of active offenders (i.e., those who are thinking about committing some crime have less incentive to do so, while those who are already involved in criminal networks have less incentive to commit a crime near to the new facilities).

The combination of these mechanisms and factors contributed significantly to the crime reduction following 2004. Although this time period was an era of continuous policy making and institutional-level work directed toward reducing crime rates, and though it happened to coincide with a quiet period between the government and crime syndicates that reduced crime in the city (Urrego et al., 2016), we still cannot disregard the fact that the decrease in homicides in the area of the new public transportation system was much higher compared to the rest of the city.

Unit of analysis: Ideally we would like to use neighborhoods as the unit of analysis, yet two factors restraint from doing tihs. First, in order to obtain socioeconomic variables we depend on a city household survey which is representative at an aggregate level called comuna (a comuna is an intermediate level of disaggregation between city and neighborhoods). Second, our empirical strategy requires to have similar geographical units overtime and neighbourhoods may change.

In order to cope with these limitations, we employ a strategy called Max-p-regions, model developed by Duque et al. (2012a). The Max-p-regions model, is a mixed integer programming (MIP) model formulated to design analytical regions by aggregating basic spatial units into the maximum number of spatially contiguous regions such that (1) each regions contains at least a predefined number of observations, and (2) the observations assigned to the same regions are homogeneous in terms of a set of attributes (e.g. socioeconomic characteristics). Contrary to other techniques for delineating regions that reach spatial contiguity by maximizing compactness (i.e. the regions are forced to be as circular as possible), the max-p-regions do not impose conditions on the shape of the region. The shape of the regions in the max-p-regions is determined by the spatial patterns of the attributes that characterize the elements to aggregate. The method precludes from considering one specific observation in two regions. [2,3]

Treatment and Control Units: The treatment units then, are those spatial units that were affected by the establishment of the Metrocable and their first neighbors. As explained, we employ exogenously generated analytical units (as in Duque et al., 2012b) as our prime unit of analysis and assign as treated those units that are under the influence of the Metrocable. Yet, since we wish to control for spatial correlation between analytical units, we need to control for the effect of contiguity between analytical regions. Consequently, it is probable that some units in the control group were affected by the treatment. This can happen because the probability of one unit of being chosen for the control group based

[2] We also do a robustness check where we use neighborhoods as the unit of analysis, and the results did not change significantly. See next section for more details.

[3] Refer to Duque et al. (2013); Patiño et al. (2014); Duque et al. (2012b, 2015); López-Bazo et al. (2015); Duque et al. (2011) for a detailed analysis of Medellin using max-p regions.

on their similarities with the treatment group should increase with the proximity between them. To overcome this effect, the selection of the control group will depend also on the contiguity condition between them. Therefore, we exclude from the control units those analytical units that are contiguous to the treated units.

Mechanisms Outcomes: To approach the impact corresponding of each of the mechanism of interest we are going to use some proxies of each one. For policing enforcement, we use captures not related to homicides. As an example of the captures included in this variable are fraud, theft, and extortion-related captures. [4] For the socioeconomic mechanism, since our focus is on labor market, we use two variables that can measure different perspectives of the labor situation: first the labor income, which can account the new engage population in the labor market; and second the percentage of formal employees, defining formal as the proportion of employees who are enrolled in the social security system. These variables account for what we have mentioned previously about the spatial-mismatch theory: a better transport system allows isolated population access to job opportunities in the labor market.

B. Identification of the Problem

One of the biggest concerns when estimating the causal effect of the Metrocable on crime is the identification problem due to a non-random assignment. The goal of the Metrocable was to provide a solution to the need for greater integrated public transportation in some areas of the city. The initial Metro system connects the north and the south of the city, while the east and the west were not fully integrated within the public transportation system. The Metrocable appeared to be a solution for areas where expanding the Metro was not feasible, mainly due to geographic characteristics. Targeting less accessible neighborhoods for the treatment is a good approach for public policy; however, those with lower accessibility levels can be particularly related to high crime patterns, even more, if we measure those indicators using road network and urban planning.[5]

Perhaps, the strongest (but plausible) assumption driving the analysis is that the treatment was assigned according to geographical characteristics. The Metrocable reached neighborhoods where land was not suitable for a Metro, and where neighborhoods had less access to the integrated public transportation system. This, in turn, could lead to a problem of selection bias since the allocation of the Metrocable system was not fully random. Another identification assumption is that those neighborhoods that were treated and those that are close to the treated neighborhoods had experienced similar reduction patterns that the rest

[4] See the Appendix A for a deep analysis of the endogeneity implied between the homicides variable and the definition of captures.

[5] For detailed analysis, see Hillier (2004), who developed an interesting analysis that compared different cities' structures and urban planning with fear of crime and crime patterns in the UK. Also, Takizawa (2013) offered a crime patterns analysis based on street-level data.

of the city did during 2004, 2006 and 2012. Although some factors lead us to think this assumption is violated (the main factors are other policy interventions, such as Library Parks and the vanishing of illegal gang activities), we can assume that equivalent interventions happened in other zones of the city and directly affected the general pattern of crime reduction during that time. Behind this assumption, there is an implication: those neighborhoods that are close to the treated areas initially behaved as the rest of the city, but after a certain time, they started to converge toward the treated behavior's units.

In order to overcome these problems, we propose a Spatial Difference in Difference approach similar to Delgado and Florax (2015) and Chagas et al. (2016) which allows us including a component to capture the indirect treatment effect on near non-treated units. Those units are geographically defined, so we can expect that they have the same probability to be treated as the treatments. Given their proximity to the treated units, if the intervention is really a deterrent of crime, the indirect treatment effect on non-treated units should exist and be negative. After establishing the causal effect of the Metrocable, we move to examine the two proposed mechanisms, namely labor market outcomes (wages, informality) and the apprehension mechanism. To do so we employ a mix of both strategies in order to obtain an efficient and unbiased estimate as presented in Ferraro and Hanauer (2014) but implemented to a spatial difference in difference framework.

C. Estimation Method

In order to quantify the effect of the Metrocable in the reduction of homicides, we designed an Impact Evaluation model that considers the spatial distribution as a relevant determinant of the total homicide reduction effect. Then, we use some proxy variable for each one of the mechanism of interest to identify the impact of the treatment net of the mechanism, in that way such difference between total impact and impact net of the mechanism tells us the impact of each of the mechanisms.

In order to follow the empirical approach, we need to point out the logic of the estimation method. Our outcome variable of interest will be the ln(Homicides), since our main focus is to measure the percentage of homicides avoided due to the treatment. However, we are aware that the count of homicides is not enough, since a homicide in a populous unit of analysis is not the same that a homicide in a less populous unit. To account for that, all the estimation structure control for ln(population), that is indeed a less restricted model (notice that an analysis made on the logarithm of the homicides rate is the same that one made on the count but assuming that the coefficient of the logarithm of the population is 1).

Now, we need to understand what is behind a spatial approach that a non-spatial one does not account for? Although the spatial word already gives some clues, its importance is sometimes underestimated. Any intervention that is geographical related -it belongs to a specific place or location- has an impact on the area of influence, disregarding if the effect is indeed what it was mean to.

However, the area of influence is the tricky part, how can we define what is the area of influence? It can be neighborhoods, municipalities, urban areas, etc. But the impact does not depend on the area we define, it depends on the geographical interactions of the units where the intervention is located. Then, it is our job to identify what is the area of influence. A spatial approach can help us with that.

In a non-spatial strategy, we have to define the affected area per se. Counting for the spatial effect an intervention is not longer positive or completely negative. It can happen that an intervention is beneficial for a neighborhood, but that does not mean that it is also beneficial for those who interact with that neighborhood. Also, an intervention can seem to be outstanding and shows a great impact, but this impact can be just the side effect of a shock in one unit that is spreading across neighbors units and not because the treatment was designed in that way, it is because the spatial interaction across units is defined like that, then any strategy that can produce similar shocks will replicate the same effects i.e. if the spatial relationship is which driven all the treatment effect, then any policy that has a similar first shock will end up having similar results. Then, if we are not able to distinguish the part of the effect that is given by the treatment and the part that is consequence of the spatial link across units, any public policy advice will be blind towards the treatment rather than taking advantage of the spatial relationship.

D. Empirical Approach

Spatial Identification Strategy

We define two potential crime outcomes for any spatial region $y_i(1)$ (the crime outcome if the spatial region is affected by the Metrocable) and $y_i(0)$ (the crime outcome if the spatial region is not affected by the Metrocable). Yet, each region actually faces only one of these potential outcomes, which leads to the need of using counterfactuals, and therefore causal inference methods are useful in identifying the effect of the Metrocable.

Given the characteristics of the intervention and the available data, our empirical strategy relies on a spatial difference in difference analysis. Using a set of observable characteristics represented by a matrix X, and an error term u; our initial outcome can be modeled as following:

$$y_{it} = X_{it}\beta + u_{it} \tag{1}$$

Yet, given the characteristic of the intervention and the relevance of the relationship between spatial units to explain crime, Eq. (1) is not correctly identified. Therefore, adding a spatial factor where the outcome variable also depends on the outcome levels neighbor spatial units is required:

$$y_{it} = W\rho y_{it} + X_{it}\beta + u_{it} \tag{2}$$

Where W represents the spatial weight matrix that summarizes the spatial relationships between units. Matrix W is of dimension $N * N$, where N is the number of units of analysis; ρ is the coefficient associated with the spatial relationship (if $\rho \neq 0$ the outcome variable does not depend on its neighbors' outcome). We argue that the intervention also affects the neighbor spatial units of the treatment region. For this case, the intervention has a non-zero externality on those units that were not treated but still are close to those intervened. This can be frequent when the interventions are related to infrastructure and can be used for any population without restriction. We are able to formulate a potential outcome for treatment and control group. Then expanding the methodology presented in Dubé et al. (2014), we have the following expression:

$$y_i\left(0\right) = y_{it} + w_i \delta d_{it} \tag{3}$$

Where w_i is the row i of the spatial weights matrix W. Then, if W represents the spatial relationship among all units, w_i contains the spatial relationship between the unit i and all the others. d_{it} is a column vector that identified the treated units, it is equal to 1 for those units treated and zero otherwise. d_{it} has to be of dimension $N * 1$, while w_i is $1 * N$. The product of these two vectors summarizes if the neighbors of i were treated or not. Then δ represents the effect of having neighbors treated on the outcome of control group, and we can pool control and treatment group before treatment, writing the Eq.(2) in its matrix form:

$$Y_{it} = W \rho Y_{it} + X_{it} \beta + U \tag{4}$$

Then, using spatial strategies we can also compile the two potential outcomes in one equation defining $D_{it} = d_{it}$ as the column vector that represents the intervened units.

$$Y_{it} = W \rho Y_{it} + X_{it} \beta + \alpha D_{it} + W \delta D_{it} + U_{it} \tag{5}$$

We can estimate the Eq. (5) using a Spatial Panel Model. For this case, the Durbin specification is the most appropriate.[6]

A Spatial Difference in Difference

The Difference in Difference strategy allows the estimation of the impact of an intervention when there are unobservable factors constant over time, or at least during the pretreatment and post-treatment period. The Spatial Diff-in-Diff is not any different, nevertheless, the biggest difference lies in the inclusion of the spatial components in the analysis. Following the procedure proposed by Delgado

[6]Chagas et al. (2016) suggest that estimation should be done using the Spatial Autoregressive model, however, we believe that there exists a direct effect from the intervention to those units' neighbors of the intervened regions and not just an indirect effect through changes in crime. For detailed information about the difference between spatial panels models see Elhorst (2014).

and Florax (2015) let's start with the main equation of a Diff-in-Diff design with two observed periods:

$$Y_{it} = X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \alpha D_{it} * t_{it} + U_{it} \tag{6}$$

Where t_{it} is a time dummy equals 1 for the year after treatment and zero for the year pre-treatment, and in this scenario, the parameter α identifies the impact of the treatment. Summarizing what we had mentioned in the previous subsection, we have that the dependent variable also depends on the crime level of their neighbors, as well as the impact of the treatment should have influenced the treated neighbors. Adding these facts to Eq. (6) and also assuming the treatment is spatially correlated, we have:

$$Y_{it} = W\rho Y_{it} + X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \alpha D_{it} * t_{it} + \alpha_2 W D_{it} + \delta W D_{it} * t_{it} + U_{it} \tag{7}$$

Considering that we have a set of two periods data instead of a complete panel structure,matrix W should be transformed from the initial contiguity matrix $N*N$ to a $2N*2N$, but it still represents the spatial relationship across units, but now for the two periods of analysis. The other matrices are similar to those found in Delgado and Florax (2015). Now, we have two spatial terms that are related to the treatment. First, we wanted to include if there is any particular difference between those units spatial correlated with the treatment and the rest of the units (represented by the coefficient α_2). Second, the impact of the treatment on those units that were not treated but according to W are spatially correlated with the treatment units (associated with the coefficient δ and a spatial impact $WD = wd$), we can calculate the ATE as:

$$\begin{aligned} ATE = & [\ E(Y \mid X,\ D=1,\ t=1, WD=wd) \\ & - E(Y \mid X,\ D=1,\ t=0, WD=wd)\ ] - \\ & [\ E(Y \mid X,\ D=0,\ t=1, WD=0) \\ & - E(Y \mid X,\ D=0,\ t=0, WD=0)\ ] \end{aligned} \tag{8}$$

Before identifying the corresponding values, we should be aware that our specification also contains a Spatial Autoregressive term, so without loss of generality we can restructure any coefficient as $\alpha' = \alpha * (I - \rho W)^{-1}$.

$$ATE = \left[\alpha_0' + \alpha_1' + \alpha' + \alpha_2' + \delta' wd - \alpha_0' - \alpha_2'\right] - \left[\alpha_1'\right] = \alpha' + \delta' wd \tag{9}$$

Rewriting from the possible set of spatial impact of the treatment and showing the similitude with the exercise of Delgado and Florax (2015):

$$ATE = \alpha^{'}\left(I + \delta wd^{'}\right) \rightarrow ATE = E\left[ATE\left(wd\right)\ \mid WD\right] = \alpha^{'}(I + \delta\overline{WD}) \quad (10)$$

Then, our treatment impact will be:

$$ATE = \alpha(I - \rho W)^{-1}\left(I + \delta\overline{WD}\right) \quad (11)$$

A Theory of Mechanism

Previously, we have defined that there are some units that were treated ($D = 1$) and other units that belong to the control group disregarding if there is some externality of the intervention ($D = 0$). Also, we explained that we have two potential outcomes, $Y\left(1\right)$ and $Y\left(0\right)$, one for the treatment and the other for the control group. However, we are interested in the mechanism through which the intervention affects the output. For this purpose and based on the methodology exposed by Flores and Flores-Lagunes (2009) we define a variable S_j that represents the mechanism j through which the intervention could affect the output. Note that there exists the probability that one mechanism j that we have identified did not really affect the output variable. In this exercise, we also have two potential options of each mechanism $S_j\left(1\right)$ and $S_j\left(0\right)$. The first one represents the value of the mechanism when the mechanism was affected by the treatment, while the second one is the value of the mechanism when was not affected by the treatment. Then, the two potential outcomes, $Y(1)$ and $Y(0)$, can be expanded as following [7]

- $Y\left(1,\ S_j\left(1\right)\right)$ is the potential outcome of those who were treated if the mechanism j was affected by the treatment. This is the same group as the previous $Y\left(1\right)$.
- $Y\left(0,\ S_j\left(0\right)\right)$ is the potential outcome of the control group if the mechanism was not affected by the treatment. That is the corresponding $Y\left(0\right)$.
- $Y\left(1, S_j\left(0\right)\right)$ is the potential outcome of those who were treated if the treatment did not affect the mechanism, i.e. the treatment effects directly associated to the outcome or through another mechanism, other than S_j.

Based on Frangakis and Rubin (2002) we also condition the average treatment effect on the specific group observed for each potential mechanism outcome $\{S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}\}$, rewriting Eq. (11) we have:

[7] Extended explanation can be found in Flores and Flores-Lagunes (2009). Also Ferraro and Hanauer (2014) define a fourth group that represents the counterfactual of what would be the potential outcome of those not treated but the mechanism j had been affected by the treatment. Given that in our analysis we already assumed that the intervention affected not treated through the spatial relation between neighbors, this counterfactual does not add significant information, so we follow the strategy of Flores and Flores-Lagunes (2009).

$$
\begin{aligned}
ATE = &E\left(Y\left(1, S_j\left(1\right)\right)|X, D,\ t, WD, S_j\left(1\right) = s_{j1}\right) - \\
&E\left(Y\left(0, S_j\left(0\right)\right)|X, D, t, WD, S_j\left(0\right) = s_{j0}\right)
\end{aligned} \tag{12}
$$

$$
\begin{aligned}
ATE = E[&Y\left(1, S_j\left(1\right)\right) - Y\left(0, S_j\left(0\right)\right)| \\
&X, D, t, WD, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}]
\end{aligned} \tag{13}
$$

In order to identify the relevance of the mechanism j we can rewrite the latest equation as following:

$$
\begin{aligned}
ATE = E[&Y\left(1,\ S_j\left(1\right)\right) - Y\left(1, S_j\left(0\right)\right) + Y\left(1, S_j\left(0\right)\right) - Y\left(0, S_j\left(0\right)\right)\ | \\
&X, D, t, WD, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}]
\end{aligned} \tag{14}
$$

$$
\begin{aligned}
ATE = &E[\\
&E[Y\left(1,\ S_j\left(1\right)\right) - Y\left(1, S_j\left(0\right)\right)\ |\ X, D, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}] + \\
&E[Y\left(1, S_j\left(0\right)\right) - Y\left(0, S_j\left(0\right)\right)\ |\ X, D, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}] \\
&]
\end{aligned} \tag{15}
$$

The first term of the last equation reflects the component of the average treatment effect that is due to the mechanism j affected by the treatment. It is the component that evidences the impact of the treatment in the outcome variable through the mechanism j. Notice that if the mechanism j is not a mechanism through which the intervention acted $S_j(1) = S_j(0)$ and the first part will be zero. The second term of the equation keeps the same level of S and estimate the difference in the potential outcomes of the treatment and control group. This is the effect of treatment on the outcome that does not belong to the mechanism j, instead, it is what we can call net average treatment effect (NATE), the ATE net of the mechanism j. Defining the mechanism average treatment effect (MATE) and NATE we have:

$$
\begin{aligned}
MATE = E[&Y\left(1,\ S_j\left(1\right)\right) - Y\left(1, S_j\left(0\right)\right)\ | \\
&X, D, t, WD, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}]
\end{aligned} \tag{16}
$$

$$
\begin{aligned}
NATE = E[&Y\left(1, S_j\left(0\right)\right) - Y\left(0, S_j\left(0\right)\right)\ | \\
&X, D, t, WD, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}]
\end{aligned} \tag{17}
$$

$$
ATE = MATE + NATE \tag{18}
$$

The biggest challenge to estimate this is that $Y(1, S_j(0))$ is not observable. We have to design a strategy to estimate the potential output that treated units would have if the mechanism j had not been affected by the treatment (NATE). Then using ATE for previous analysis we will obtain MATE.

To address this issue, we first assume that the assignment of the treatment is independent of the potential outcomes given a set of covariates X and the observed post-treatment values of the mechanism.

$$Y\left(1, S_j\left(1\right)\right), Y\left(0, S_j\left(0\right)\right), Y\left(1, S_j\left(0\right)\right) \perp \left\{D, S_j\left(1\right), S_j\left(0\right)\right\} \mid X, t, WD \tag{19}$$

We rely in the existence of a functional form for $Y(1, S_j(1))$ and $Y(0, S_j(0))$, where:

$$E\left[Y\left(1, S_j\left(1\right)\right) \mid S_j\left(1\right) = s_{j1},\ X, t, WD\right] = f_1\left(S_j\left(1\right), X, t, WD\right) \tag{20}$$

Using this expression we can estimate the unobservable potential outcome as following:

$$E\left[Y\left(1, S_j\left(0\right)\right) \mid S_j\left(0\right) = s_{j0},\ X, t, WD\right] = f_1\left(S_j\left(0\right),\ X, t, WD\right) \tag{21}$$

In order to use the spatial specification already presented in the last subsection, we similarly define the Eq. (20) for the control group:

$$E\left[Y\left(0, S_j\left(0\right)\right) \mid S_j\left(0\right) = s_{j0},\ X, t, WD\right] = f_0\left(S_j\left(0\right), X, t, WD\right) \tag{22}$$

Keeping in mind that we are analyzing two similar groups where the treatment was conditional randomly assigned based on some observables characteristics X, we believe that the functional form of the treatment group presented in Eq. (21) is equivalent to the control group in Eq. (23) when a dummy variable is added which equals one if the unit was treated and zero otherwise.

$$f_1(S_j(1), X, t, WD) = f(S_j(1), X, D = 1, t, WD) \tag{23}$$
$$f_0(S_j(0), X, t, WD) = f(S_j(0), X, D = 0, t, WD) \tag{24}$$

Using Eq. (8) we can define the functional form as following:

$$\begin{aligned} f(X, D, t, WD) = & Y_{it} = \\ & W\rho Y_{it} + X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \alpha D_{it} * t_{it} + \\ & \alpha_2 WD_{it} + \delta WD_{it} * t_{it} + U_{it} \end{aligned} \tag{25}$$

Letting $g(S_j)$ represents how the mechanism enters in the functional form, we will have:

$$\begin{aligned} f(S_j, X, D, t, WD) =& Y_{it} = \\ & W\rho Y_{it} + X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \alpha D_{it} * t_{it} + \\ & \alpha_2 WD_{it} + \delta WD_{it} * t_{it} + \gamma g_{it}(S_j) + U_{it} \end{aligned} \tag{26}$$

As a simple way to approach this equation, we can assume that $g_{it}(S_j) = S_{j,\ it}$; but we can also say that $g_{it}(S_j) = S_{j,it} + S_{j,it}X_{k,it}$ summarizing that the mechanism affects the potential output also through an interaction with a predetermined variable x_k. Or in a more complex way, that is not the objective of this paper, the mechanism affects directly not only the unit i but also its neighbors $g_{it}(S_j) = S_{j,it}\ + WS_{j,it}$. But the bottom line of using $g_{it}(S_j)$ is that in next steps we will need to apply some restriction on $g_{it}(S_j)$ to net the impact from the effect of the mechanism, so defining it as an external independent function allows us to simplify the estimation of NATE.

Decomposing the definition of NATE, we have:

$$\begin{aligned} NATE =& E[E[Y(1, S_j(0)) \mid X, D, t, WD, S_j(0) = s_{j0},\ S_j(1) = s_{j1}] \\ & - E[Y(0, S_j(0)) \mid X, D, t, WD, S_j(0) = s_{j0},\ S_j(1) = s_{j1}]] \end{aligned} \tag{27}$$

$$\begin{aligned} NATE =& E\{E[Y(1, S_j(0)) \mid X, D, t, WD, S_j(0) = s_{j0},] - \\ & E[Y(0, S_j(0)) \mid X, D, t, WD, S_j(0) = s_{j0}]\} \end{aligned} \tag{28}$$

$$\begin{aligned} NATE =& E\{f_1(S_j(0),\ X, t, WD) - \\ & E[Y(0) \mid X, D, t, WD, S_j(0) = s_{j0}]\} \end{aligned} \tag{29}$$

Note that the last expression can be represented with the functional form (Eq. (23) keeping the values $S_j(0)$ constant.

$$NATE = E\{f_1(S_j(0),\ X, t, WD) - f_0(S_j(0), X, t, WD)\} \tag{30}$$

Using the Eq. (24) and Eq. (25), we will have:

$$NATE = E\{f(S_j(0), X, D = 1, t, WD) - f(S_j(0), X, D = 0, t, WD)\} \tag{31}$$

Given the functional form expressed in Eq. (26) and in order to feasible estimate the impact net of the mechanism, let us show the equation just for the period pretreatment:

$$Y_{i0} = W\rho Y_{i0} + X_{i0}\beta + \alpha_0 D_i + \alpha_2 W D_i + \gamma g_{i0}\left(S_j\right) + U_{i0} \tag{32}$$

Now, this will be the equation just for the post-treatment period:

$$Y_{i1} = W\rho Y_{i1} + X_{i1}\beta + (\alpha_0 + \alpha) D_i + \alpha_1 + (\alpha_2 + \delta) W D_{i1} + \gamma g_{i1}\left(S_j\right) + U_{it} \tag{33}$$

We are interested in the mechanism term of the post-treatment specification. We rely on the fact that if the mechanism is a real and significant mechanism through which the treatment has affected the outcome, we will have two option about how to treat this situation:

- Option 1: for the transition between Eq(32 and 33) the structure of the mechanism variable has changed, leading that the parameter γ of the first one is not the same that the second one.

- Option 2: for the transition between Eq(32 and 33) the structure of the mechanism variable has not changed, so the parameter γ is constant across the specification and what has been affected is the level of the variable.

We rely on the option 2 for the purpose of our analysis and arguing that the structure of a mechanism is a much more difficult thing to modify with an intervention. In this sense is really feasible to us calculate the Net Average Treatment Effect. We first obtain the value of γ and then we have:

$$\begin{aligned} f(S_j, X, D, t, WD) = Y_{it} =& W\rho Y_{it} + X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \alpha D_{it} * t_{it} + \\ & \alpha_2 W D_{it} + \delta W D_{it} * t_{it} + \bar{\gamma} g_{it}\left(S_j\right) + U_{it} \end{aligned} \tag{34}$$

And given that this term $\bar{\gamma} g_{it}\left(S_j\right)$ is now a constant we can rewrite as following:

$$\begin{aligned} \left(Y_{it} - \bar{\gamma} g_{it}\left(S_j\right)\right) =& W\rho\left(Y_{it} - \bar{\gamma} g_{it}\left(S_j\right)\right) + X_{it}\beta + \alpha_0 D_{it} + \alpha_1 t_{it} + \\ & \alpha D_{it} * t_{it} + \alpha_2 W D_{it} + \delta W D_{it} * t_{it} + U_{it} \end{aligned} \tag{35}$$

And the NATE will be similar to the ATE calculated in the Eq (11), but keeping in mind that the mechanism effect has been subtracted from the dependent variable. Then, the difference between this new estimation and the previous one will represent the impact of the treatment through this mechanism.

$$NATE = \alpha\left(I + \delta\overline{WD}\right)(I - \rho W)^{-1} \tag{36}$$

IV. Dataset

The main input for our analysis is homicide rates. We collect georeferenced homicide data in the city of Medellin for the available period (2004 - 2012). This data is obtained from the Sistema de Información para la Seguridad y Convivencia (SISC) from the Municipality of Medellin. We supplement this information with data from the Quality of Life survey for the city of Medellin (for years 2004, 2005, 2006 and 2012). These last sources are key in order to obtain appropriate covariates as well as labor market outcomes. Thus, we use 2004 as the baseline for our study.

Baseline and post-treatment: Our baseline dataset consists of information about homicides, arrests, and robberies and for labor market outcomes in 2004. The source for labor market outcomes is the city of Medellin household survey for the year 2004. This survey was implemented right before the Metrocable began operations (in 2004), which provides an adequate baseline. In order to examine short and medium run effects, we employ the household surveys for 2006 (as short-run effects) and the Medellin Household Survey for 2012 (as medium-run effects).

V. Results

As a preliminary fact, the number of homicides happening within 1 kilometer radius of the metro stations differs between Metrocable and train stations. For the initial two lines of the train, Line A and Line B, the number of homicides decreased on average 24.5% and 11.3% between 2003 and 2004, respectively. However, this reduction is higher if we focus on Metrocable stations. If we analyze the number of homicides that occurred in the same area in 2003, before the construction, and compare this figure to the number of homicides after the Metrocable was opened in 2004, the reduction is, on average, 61.8%. Although this effect may not only be driven by the construction of the new facilities, this difference was persistent until the next year. The decline in the number of homicides around 1 kilometer of the Metro stations Line A and Line B between 2004 and 2005 were 34.1% and 37.8%, respectively. Over the same period, for the Metrocable stations, the decrease was 50% on average.

The Figure 1 is related to what we have mentioned above. It shows the Kernel Density distribution of the homicides respect to how far they happened from a Metro or Metrocable station. This graph is a particularly good starting point, it marks the fact that the distribution of homicides over the distance to public transport system stations does not seem different across years. This is strongly related to the fact that this intervention led to a reduction of homicides instead of displacement of them. This figure also marks the average distance from Metrocable stations to the treated, first neighbors, second neighbors, and third neighbors units (see Figure 2 to identify in the maps what first, second and third neighbors geographically mean). [8] Also the Table 1 complements this information showing the average distance between first, second and third neighbors respect to the Metrocable stations. First neighbors are defined as those units which share a border or a vertice with the treated units, second neighbors are those that share a border or a vertice with the first neighbors; and third neighbors are the adjacent units of the second neighbors. It is evident that the most concentration of homicides has been happening between the treated and first neighbors units. Then, if the Metrocable had an impact on homicides, we should identify a non-zero reduction mainly in first neighborhoods.

Figure 3 shows the geographical distribution of homicides in Medellin for the years 2004, 2006, and 2012. These maps highlight the Metro system that divides the city and that was built on 1995. Following 2004, the Metro system includes other lines which represent the new Metrocable public transportation system. The maps show a reduction in the number of homicides through the city and a change in its pattern. There was a movement of homicides to areas that were "safer" at the beginning. In addition, homicides for 2004 were highly concentrated in certain areas of the city, some of them coincide with the Metrocable stations. As for 2006, a decrease in the area related with the Metrocable is evident while for 2012 a slight increase can be identified. These findings are a first hint on the effects of the Metrocable in the affected areas.

Table 1—: Sample Sizes and Distance Distribution of Units

	Mean distance to nearest Metrocable Line K station (Km)		**Number of geographical units in group**	
Group	Neighborhoods	Maxp 30	Neighborhoods	Maxp 30
Treated	0.38	0.40	7	6
1st Neighbors	0.69	0.77	11	11
2nd Neighbors	1.15	1.33	13	10
3rd Neighbors	1.84	2.18	9	14
Others	6.65	6.82	186	135
Total			226	176

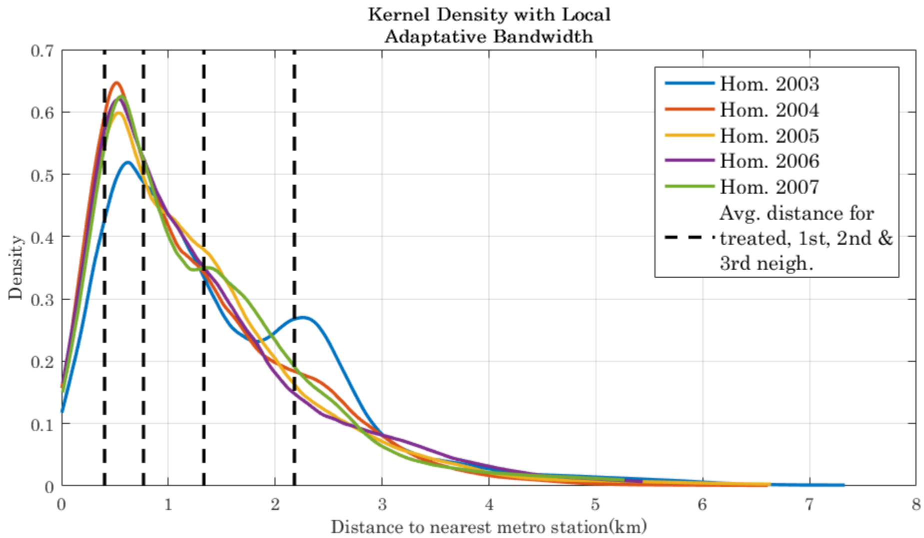
Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Distance is presented in kilometers. Maxp 30 refers to the units calculated using the Max p method. The figures in the columns of number of geographical units mean the number of neighborhoods or maxp regions inside each of the group of analyis.

A. Summary Statistics

Table 2 presents the summary statistics of our dataset. The trend in homicides at our spatial unit shows a larger decrease between 2004 and 2006 than

[8]For a deep detailed analysis about degree of neighborship see Anselin and Smirnov (1996)

Figure 1. : Homicides Kernel Density by Year

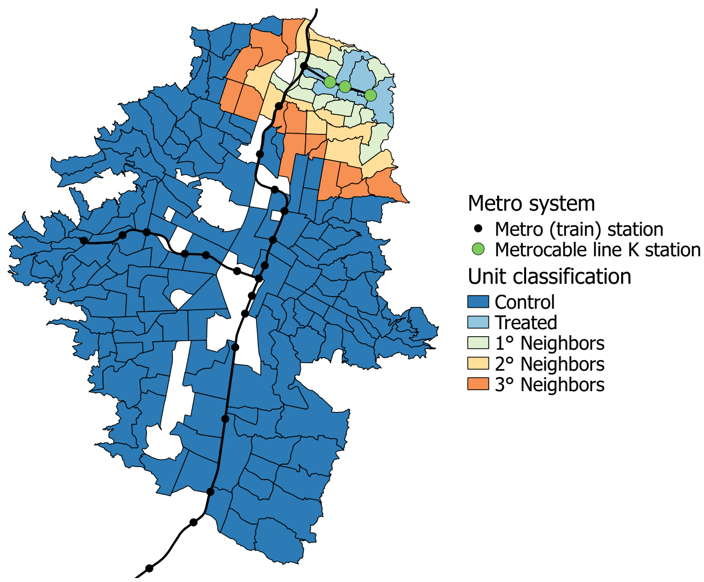


Source: author's calculation
Note: the solid lines represent the homicides density according to the distance to the nearest Metro or Metrocable station by year. The black dotted lines represent the average distance between the defined treated, first, second and third neighbors units.

between 2004 and 2012. As for socioeconomic factors such as labor income, we identify a pretty stable behavior with a slight, not significant, decrease in labor income between 2004 and 2012. Other factors such as the percentage of informality go pretty much in line with the Medellin's experience, where most of the working population are in the informal sector. The share of married population changes slightly over time with about 25 percent of the population being married. Our summary statistics show that education lags behind in Medellin. About 70 percent of youngsters (from 15 to 19 years old) do not attend school and the percentage of population with secondary (complete or incomplete) is around 47 percent.

However, these results hide some heterogeneity across treated and untreated units. In an exhaustive analysis of means and summary stats broken down by treatment and control groups we found that in our baseline, homicides are higher in spatial units that are treated compared to those in untreated spatial units. However, after the implementation of the Metrocable, treated units present slightly fewer homicides compared to those untreated ones. As for labor income, untreated units show higher levels compared to treated ones over the entire period of analysis. Some of our socioeconomic covariates show differences between untreated and treated groups related to the cultural and economic characteristics

Figure 2. : Mapping of Treated, First, Second and Third Neighbors; and Control Units



Source: author's calculation
Note: The definition of the first, second and third neighbors is given by a share-border criteria. First neighbors are those who share at least one border or vertice with the treated units. Similar, second neighbors are those who share at least one border or vertice with the first neighbors.

of poor areas. Married population is higher in the treated areas, as well as the percentage of secondary education. The number of children are also higher in regions that were treated compared to the untreated ones. [9]

As a complementary resource to the summary table, Figure 4 shows the homicide rate per 100,000 inhabitants for two groups of neighborhoods. One group that is composed of the neighborhoods treated plus the first neighbors of the treated units, this is defined following the preliminary findings in Figure 1, where homicides are more concentrated in first neighbors units. The other group is called control, and this group contains all the neighborhoods not included in the first one. Although the rates are a little bit noisy, it is evident that before the treatment both groups had a negative trend, being the treated more violent than the control group. Then, after the treatment those neighborhoods in the control group stay at a constant pace and having a greater homicides rate for almost all the following periods.

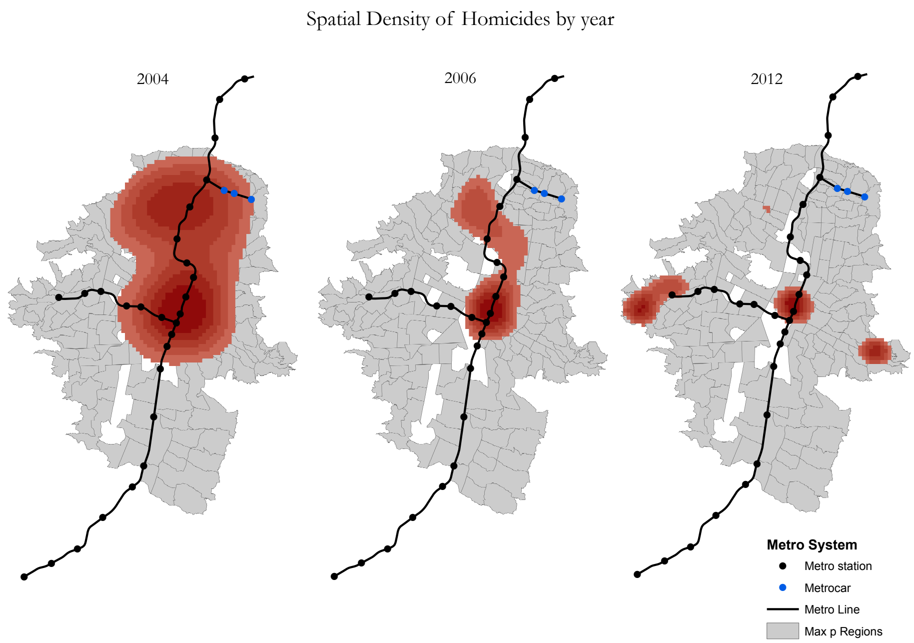
[9] Complete summary tables upon request.

Table 2—: Summary statistics

Variable	N	Mean	Std. dev.	Min	Median	Max
		2004				
ln(Homicides + 1)	176	1.60	0.77	0	1.61	3.78
ln(Labor Income)	176	13.14	0.51	12.40	12.99	14.97
ln(Captures)	176	3.19	0.97	0	3.18	6.95
% Employees with social security	176	70.16	13.52	19.86	70.94	98.01
ln(Population)	176	9.13	0.66	6.39	9.21	10.50
% Married population	176	25.04	7.21	5.23	24.56	45.77
% Male population	176	45.20	2.96	35.22	45.40	53.06
% Secondary incomplete	176	20.12	5.30	7.69	21.16	35.05
% Secondary complete	176	25.33	8.58	5.33	26.54	42.57
% Young 15-19 not assisting school	176	71.76	16.61	9.18	72.33	100
% Population with social security	176	15.81	7.92	1.75	14.71	41.51
Average number of children	176	2.00	0.37	0.99	1.99	3.21
		2006				
ln(Homicides + 1)	176	1.27	0.82	0	1.39	3.53
ln(Labor Income)	176	11.94	0.58	9.98	11.87	13.70
ln(Captures)	176	2.41	1.15	0	2.48	7.04
% Employees with social security	176	59.92	14.12	24.33	58.92	98.86
ln(Population)	176	9.14	0.62	7.13	9.08	10.60
% Married population	176	25.21	6.67	7.73	24.61	42.66
% Male population	176	45.85	2.43	36.87	46.14	51.85
% Secondary incomplete	176	14.85	3.84	5.07	15.19	22.83
% Secondary complete	176	26.44	8.28	5.56	26.68	47.48
% Young 15-19 not assisting school	176	74.29	13.91	31.82	73.90	100
% Population with social security	176	18.14	8.45	0.39	17.65	44.84
Average number of children	176	1.94	0.32	1.03	1.96	2.62
		2012				
ln(Homicides + 1)	176	1.55	0.85	0	1.61	3.69
ln(Labor Income)	176	12.88	0.64	11.96	12.69	14.74
ln(Captures)	176	2.85	1.02	0	2.83	6.52
% Employees with social security	176	42.59	15.48	6.19	44.39	81.24
ln(Population)	176	9.14	0.52	7.59	9.09	10.40
% Married population	176	25.09	8.79	6.72	24.21	49.86
% Male population	176	46.84	2.98	38.66	46.98	54.50
% Secondary incomplete	176	14.57	5.23	2.49	15.01	29.26
% Secondary complete	176	23.91	5.58	10.84	23.84	42.81
% Young 15-19 not assisting school	176	75.05	16.44	21.77	75.41	100
% Population with social security	176	25.64	9.99	7.55	24.23	62.84
Average number of children	176	1.67	0.36	0.75	1.67	2.69

Source: author's calculation
Note: this summary table is just for the principal variables used and does not disregard if the geogaphical unit is treated or not. However, a complete summary stats for all the variables and broken down by control, treatment, first, second and third neighbors is available upon request.

Figure 3. : Spatial Density of Homicides in Medellin for 2004, 2006, and 2012.

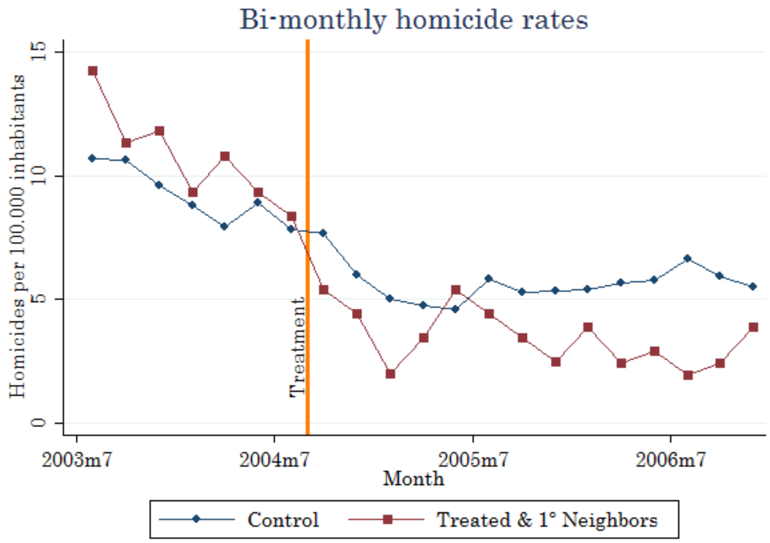


Source: author's calculation
Note: this figure is made using a spatial kernel. The interpretation is focused mainly in the concentration and intesity of the color rather than some specific values. Intense red means highest density of homicides, while lighter red means less density of homicides in that area. The concentration is presented where there is something colored red. i.e. we first identify the area where the homicides are concentrated, if they are, and then we categorize the intensity of the concentration in that area.

B. Main Results

Table 3 presents the results of the estimations using treated units, treated plus first spatial neighbors, treated plus two spatial neighbors and treated plus 3 spatial neighbors units. We depart from a regular difference in difference estimate which does not consider the spatial component. Although all the results in the first panel of Table 3 refer to common Difference in Difference approach, only the first column of results, that are those for treated, belong to the strict OLS estimation. The results for treated plus neighbors though they were estimated using an OLS strategy, they account for a spatial relationship (not necessarily the estimator has to be defined with an spatial matrix to make the results include some spatial relationship). These results represent what is commonly labeled as "naive" specification, the model does account for spatial relationship, but the estimation strategy will probably not be the most unbiased. Nevertheless, we refer to OLS result to the complete set of common Difference in Difference set.

Figure 4. : Pre & post-treatment behavior of homicides



Source: author's calculation
Note: the treatment line were defined as treated plus first neighbors according to the density of homicides discussed before. The homicides rates are bi-monthly to avoid some noisy from the monthly rates and to provide a zoom view from the yearly rates.

Our preliminary estimates for the immediate short run (2006) for the common Dif-in-Dif, show a negative effect of the cable cart in terms of homicide reduction, yet not statistically significant. The point estimates suggest that the implementation of the cable cart did not have an effect on the treated units alone (which could be guided by the small sample of treated units), but had a large and statistically significant effect when considering the treated and first neighbors units; the effect vanishes when the second and third neighbors are included. As for the medium run effects (2012) results from the OLS estimates are much encouraging, while we do not find any statistically significant effect for the treated units, when including first, second and third neighbors the impact of the Metrocable is strongly significant and also much larger than those identified in the short-run. In fact, we could infer that for first neighbors the homicide decreased by 51 percent[10], an effect which declines as we include second spatial neighbors reaching a total impact of 44 percent and finally, after including third spatial neighbors the impact is 46 percent.

However, as it was presented in the methodological section OLS estimates can

[10]Remember that interpreting log-linear model with dummies require the transformation of the dummy 100[exp(c) - 1]

be biased since they do not strictly account for spatial correlation that exists in the data. Therefore, following we present estimates considering a Spatial Difference in Difference approach. Table 3 presents these results in the second panel set. The conclusions that can be obtained from these numbers are similar (for the most part) to the ones of the OLS estimates but more significant and slightly smaller. We find small and not statistically significant results for the immediate short run estimates while we find strong and larger effects overt time. For the short run we find a statistically significant effect of 42 percent for treated and first neighbors spatial units, however, no statistically significant effect is found when considering second and third neighbors. This finding is aligned with our hypothesis stated in previous subsections, where we showed that the homicides' density is more concentrated on treated and first neighbors allowing us to identify particular changes, meaning that second and third neighbors are not affected immediately.

As for the medium run effects, we find significant and negative effects for the first, second and third neighbors. When considering the spatial interactions, the Metrocable has reduced crime in first neighbors by 49 percent while, when considering the second neighbors this effect is reduced to 43 percent and for third neighbors the impact goes up until 45 percent (yet still strongly statistically significant). We should mention that these figures should be taken carefully and not misunderstand their meanings. The 43 percent reduction found in treated plus second neighbors, first it does not mean that the Metrocable almost half the homicides in that area, the meaning is that the homicide's decrease is 43 percent more than in the control group, then if the control had decreased 20 percent, the treatment should have decreased by 29 percent. Second, we refer to treatment plus second neighbors to all the geographic area from directed treated units until second neighbors, that includes first neighbors as well. So, the 43 percent is the coefficient for all that area. In the next section we divided the impact, area per area in order to corroborate that there is not evidence of crime displacement.

Another important finding we can observe from Table 3 is given by the behavior of the standard errors. The standard errors go down sharply as we move from treatment units to third neighbors This is a particularly strong evidence that the statistical power increases, showing that it is really likely that the coefficient of treatment is indeed negative, but due to the small sample we fail in obtaining statistical significance.

In sum, we find stronger and sizeable effects in homicide reduction close to the Metrocable area which tends to reduce across space and time. Our Spatial Difference in Difference model including controls as covariates shows a reduction of around 49% in the neighborhoods that are treated by the Metrocable and those first level neighbors, then when we move to a greater influenced area the impact decreases 7 percentage points, to then increases 2 percentage points when we go up to third neighbors. This shows evidence for a spatial decay function of the Metrocable and a time increase over time.

Table 3—: Results for common and Spatial Difference in Difference

Dependent: ln(Homicides+1)	**Treated**	**Treated + 1st Neighbors**	**Treated + 2nd Neighbors**	**Treated + 3rd Neighbors**
Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	-0.41	-0.53**	-0.18	-0.10
	(0.27)	(0.21)	(0.20)	(0.18)
	-33.80%	-41.19%	-16.48%	-9.44%
		Medium Impact (2004-2012)		
Total Impact	-0.66*	-0.71***	-0.59***	-0.62***
	(0.38)	(0.23)	(0.20)	(0.18)
	-48.30%	-50.97%	-44.35%	-45.97%
Spatial Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	−0.42	−0.54***	−0.23	−0.13
	(0.28)	(0.21)	(0.19)	(0.17)
	−34.13%	−41.77%	−20.19%	−11.97%
		Medium Impact (2004-2012)		
Total Impact	−0.58	−0.68***	−0.56***	−0.60***
	(0.40)	(0.23)	(0.20)	(0.18)
	−43.99%	−49.38%	−42.80%	−45.25%
Number of treated units	6	17	27	41
Number of control units	170	159	149	135

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages are calculated using the formula to approximate the marginal impact of a dummy in a log functional form.

C. Mechanisms

As was presented in the previous subsection, the implementation of the Metrocable reduced crime in the affected areas (first, second and third neighbors) by about 49, 43 and 45 percent. We decompose this impact into its constituent mechanism effects; i.e., we clarify the causal pathways through which this reduction in homicides was achieved. We consider two mechanisms related to policing and economic changes. As we mentioned in the first sections of this paper, many other mechanisms can have played an important role in the decreasing of crime due to the Metrocable intervention. However, we just focus on these two, that are those which represent remarkable topics in crime analysis: labor income and police efficiency.

Table 4 shows the total impact estimated for the short and medium run, also each of the impacts is broken down by what we have called NATE, the average treatment effect net of the mechanism. For each time period of analysis, we have the impact net of the socioeconomic mechanism, the police mechanism and net of both mechanisms. The exercise for net of both mechanisms is done in order to corroborate the relevance of the mechanisms identified and the accurate estimation of each of the impacts. If both mechanisms, indeed are relevant to explain why the new Metrocable led on improvements in the crime in that area, the difference between the total impact and the impact net of both mechanisms should be close enough to the sum of the individual impact of each of them separately. That is why also we cannot have many mechanisms since that would decrease the ability to check their significance in this way.

Socio-Economic Mechanism: One of the mechanisms through which the Metrocable can be affecting homicides is the inclusion of people in the city. People are able to access jobs as well as increase productivity due to a reduction in transportation costs such as time and available income. In order to explore this mechanism, we use labor income and the percentage of formal employees. As it can be inferred from table 4, in the short run for the treated units and their first neighbors around 12 percent of the total effect can be attributed to the economic mechanism, an effect that tends to be reduced in the medium run until 3 percent. In the short run, the reduction for all the area until second and third neighbors are 23 and 29 percent respectively, though these figures are not statistically significant.

The effect almost disappears in the medium run for the second and third neighbors. Despite, we can think that the effect will remain over time, but we should be aware that the mechanism collects what we refer to the spatial-mismatch theory, in which those that were isolated faced more difficulties to find a job or to enter in the legal labor market, while those far away of the isolated population may not face the same problem, or at least not as deep as the treatment units.

Deterrent Mechanism: The second potential mechanism for homicide reduction deals with deterrence. The implementation of the Metrocable also acts as a deterrence mechanism due to the increasing number of policemen in the area. This, in turn, may result in a larger number of arrests. We find that near 22 percent of the effect for treated plus first neighbors can be explained by this mechanism in the short run, however, this effect reduces to 12 percent in the medium run. The impact is particularly greater for second and third neighbors. For the medium run, in which all the coefficients remain statistically significant, 17 percent and 24 percent of the total reduction in the homicides due to the treatment for the treated plus second neighbors and third neighbors, respectively, can be attributable to the deterrent mechanism.

The new facilities are not only equipped with surveillance cameras, also there is the permanent presence of the police. Those policemen are in charge of the security inside and in adjacent zones to the station. All stations have an open wide access through the mobility and visibility is a prior characteristic. Although, that police force is not allowed to make rounds around the neighborhood, their presence acts as a deterrent for those incipient criminals, mainly those that are really concern about being caught. The prevalence also of the impact is a clear evidence that crime displacement seems to do not take place in this analysis. We further analyze this concern.

As mentioned early, the impact of both mechanisms together (socioeconomic and deterrent) is really close to the total impact by each individual mechanism, evidence of the relevance and accuracy of the estimations. Both mechanisms in the short run for treated units plus first neighbors account for 42 percent of the total intervention's impact. Although this figure goes down in the medium term, the impact spreads to adjacent zones. Then both mechanisms account for 19 percent, 19 percent and 25 percent of the total intervention's reduction in the medium run for treated plus first, second and third neighbors, respectively. Concluding that some part of the impact will vanish over time, but in a spatial framework that impact should have some effect on those units which are linked somehow to the units treated.

Table 4—: Mechanism decomposition within the Spatial Difference in Difference

Dependent: ln(Homicides+1)	**Treated**	**Treated + 1st Neigh.**	**Treated + 2nd Neigh.**	**Treated + 3rd Neigh.**
	Short Impact (2004-2006)			
Total Impact	−0.42	−0.54***	−0.23	−0.13
	(0.28)	(0.21)	(0.19)	(0.17)
	−34.13%	−41.77%	−20.19%	−11.97%
Net of Economic mechanism	−0.38	−0.48**	−0.17	−0.09
	(0.27)	(0.21)	(0.19)	(0.17)
	−31.72%	−37.92%	−15.90%	−8.65%
Net of Police mechanism	−0.38	−0.42**	−0.17	−0.07
	(0.24)	(0.19)	(0.18)	(0.15)
	−31.30%	−34.44%	−15.63%	−6.64%
Net of Both mechanisms	−0.31	−0.31	−0.08	−0.00
	(0.23)	(0.20)	(0.18)	(0.16)
	−26.58%	−26.88%	−7.63%	−0.07%
	Medium Impact (2004-2012)			
Total Impact	−0.58	−0.68***	−0.56***	−0.60***
	(0.40)	(0.23)	(0.20)	(0.18)
	−43.99%	−49.38%	−42.80%	−45.25%
Net of Economic mechanism	−0.53	−0.66***	−0.56***	−0.60***
	(0.40)	(0.23)	(0.20)	(0.18)
	−41.30%	−48.35%	−42.72%	−45.37%
Net of Police mechanism	−0.45	−0.60***	−0.47**	−0.46***
	(0.39)	(0.21)	(0.18)	(0.16)
	−36.41%	−45.07%	−37.23%	−36.90%
Net of Both mechanism	−0.36	−0.55**	−0.45**	−0.45***
	(0.40)	(0.22)	(0.19)	(0.16)
	−30.38%	−42.37%	−36.27%	−36.15%

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages are calculated using the formula to approximate the marginal impact of a dummy in a log functional form. To obtain the impact of each mechanism as a percentage of the total impact, the result from the net of mechanism's coefficient over the total impact's coefficient should be subtracted from 1 and then multiply per 100.

D. Robustness Checks

Units of analysis: Neighborhoods

One of the main concerns in this study is that of the units of analysis proposed. We are working on special units called Max-p regions, and though this strategy is particularly safe in statistical terms to make analysis on geographical units at the lowest level of disaggregation allowed by the data availability, there is a concern about the results being not entirely interpretable for the public policy design perspective.

To address this matter we propose a robustness check where we use the well-defined neighborhoods of the city instead of the max-p regions units. The aim of this exercise is to check that our main results are not driven by the composition of the unit of analysis defined. Table 5 shows the results for this exercise, it shows both the common Difference in Difference and the Spatial one. Consistently, the variation between the impact estimated using max-p regions and that using neighborhood is not large.

The Spatial Difference in Difference shows a reduction of homicides of 46, 43 and 41 percent due to the intervention in the medium run for treated neighborhoods plus first, second and third neighbors, respectively. The figures for max-p regions are particularly similar: 49, 43 and 45 percent for treated units plus first, second and third neighbors, respectively.

Although some reasons were given before to support the use of max-p regions we would like to summarize them after we have checked that there is not a considerable difference between them. The first reason is statistical, we should make the analysis based on variables that are representative at the unit of analysis' level. The exercise on neighborhoods is particularly more biased due to its strong relationship with the survey design. The second is practical, due to the definition of our theory framework, all matrices are designed to work just for balance dataset, then if at any time there are not observations of one neighborhood one year, the unbalanced dataset will not allow any estimation. And finally after this test and given that there is not big difference across both options, we do not have any constraint to keep using max-p regions.

Crime Displacement

Crime displacement is one of the main questions that have to be addressed when we discuss crime reduction patterns. After an intervention which seeks to reduce crime and violence, if that reduction happens the question will be was there a clear reduction of the crime and violence levels? Or there was a displacement or movement of those crime and violence events.

Some analysis that are particularly related to police enforcement argue that increasing the police force of the vigilance would deter the criminal to commit the crime near to the zone where this is happening, but there is no guarantee that the

Table 5—: Neighborhoods as analytical units

Dependent: ln(Homicides+1)	**Treated**	**Treated + 1st Neighbors**	**Treated + 2nd Neighbors**	**Treated + 3rd Neighbors**
Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	−0.43*	−0.50**	−0.13	−0.04
	(0.23)	(0.20)	(0.17)	(0.16)
	−34.98%	−39.38%	−12.47%	−4.00%
		Medium Impact (2004-2012)		
Total Impact	−0.62*	−0.68***	−0.60***	−0.56***
	(0.32)	(0.22)	(0.18)	(0.17)
	−46.17%	−49.12%	−45.39%	−42.96%
Spatial Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	−0.40	−0.51**	−0.16	−0.06
	(0.36)	(0.23)	(0.18)	(0.17)
	−33.04%	−39.98%	−15.15%	−5.80%
		Medium Impact (2004-2012)		
Total Impact	−0.52	−0.62***	−0.56***	−0.54***
	(0.37)	(0.24)	(0.19)	(0.18)
	−40.65%	−46.12%	−43.13%	−41.43%
Number of treated units	7	18	31	40
Number of control units	219	208	195	186

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages are calculated using the formula to approximate the marginal impact of a dummy in a log functional form.

criminal will not commit the crime at all. The perpetrator can move far enough from the place where the police are and commit the crime. In order to test how feasible this theory is, we run our main estimation in a sequential way. i.e. that instead of the coefficient estimated applied for all the zone between treated and first, second or third neighbors, we are going to estimate the coefficient for each one. Then, for treated plus first neighbors we will have two coefficients: the one for treated and the one for first neighbors; similarly for treated plus second neighbors we will have three coefficients: treated, first neighbors and second neighbors; the same applies for treated plus third neighbors. Notice that although this exercise allows us to identify changes in the impact for each area, we will increase the number of coeffcients needed to estimate; that will cost us some efficiency in the estimators.

Table 6 shows the results for this robustness check. The aim of this exercise is that the coefficient estimated for each group does not weaken when we add a further zone in the analysis, and we refers as weakening in terms of magnitude of the coefficient and the low standard errors. As we can see, each time that more units are included in the influenced area by the treatment, the treated impact although is not significant it remains fairly constant across specifications. Same happened to first neighbors, for which the impact is significant and it clearly intensifies as we move further. If criminal displacement were happening, when we move further the previously estimated coefficient will decrease or become more noisily, or at least one coefficient of the further zones will be positive. So, there is not incipient evidence of crime displacement, meaning that the reduction was indeed in the violence and crime levels.

Another concern related to crime displacement is the permanent change of criminal's residence. Crime displacement not only refers to the fact that the crime will happen in another place, also that the criminal moves to another neighborhood. In this case, it can happen that some criminals due to the increasing in the presence of police have migrated to other neighborhoods. Using the data from the Quality of Life survey we found that in 2006 the level of migration in the neighborhoods treated was 7.49% while for neighborhoods not-treated nearby this figure was on average 10 percent. For 2012, those treated experienced a slight increase in migration to 9 percent, but for those nearby not-treated the percentage was 11. We can infer for those figures that migration is not a really concern in this analysis, for now.

Table 6—: Sequential estimations.

Dependent: ln(Homicides+1)				
	Short impact (2004-2006)			
	Treated	1st Neighbors	2nd Neighbors	3rd Neighbors
Treated + 1st Neighbors	−0.44	−0.59**		
	(0.40)	(0.30)		
Treated + 2nd Neighbors	−0.43	−0.57*	0.30	
	(0.40)	(0.30)	(0.32)	
Treated + 3rd Neighbors	−0.42	−0.56*	0.34	0.03
	(0.41)	(0.31)	(0.33)	(0.28)
	Medium impact (2004-2012)			
	Treated	1st Neighbors	2nd Neighbors	3rd Neighbors
Treated + 1st Neighbors	−0.63	−0.71**		
	(0.41)	(0.31)		
Treated + 2nd Neighbors	−0.68	−0.73**	−0.32	
	(0.42)	(0.31)	(0.33)	
Treated + 3rd Neighbors	−0.79*	−0.79**	−0.38	−0.53*
	(0.42)	(0.32)	(0.33)	(0.28)

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. For each row named as Treated plus first, second and third neighbors the impact of each group is estimated separately, e.g. the last row of Treated + 3rd Neighbors has 4 coefficients related to, the first one of just for the treated units, the second one belongs to first neighbors alone, third coefficient for second neighborhoods and fourth coefficient for the impact on just third neighbors.

Genetic Matching

This robustness check aims to corroborate that the results found were not driven by the number of control units included. Although for all of our main results we keep the control group as all those units that are not in the treatment group and belong to the urban area of Medellin city, some doubts emerge about the convenience of this assumption. We preferred to address the analysis in that way because it allows us to make some general conclusions about the reduction of homicides due to the Metrocable respect to the general decreasing crime levels of the city. But also, as we have mentioned before, the amount of control units over the treated had reduced our statistical power to find strong significant impact on the treated units alone. In contrast to this, there are some other studies that used a considerable low ratio between treated and control units. [11]

So, to address this limitation we implement a genetic matching to find a reduce control group between all the units we have available and then applied our methodology to estimate the impact. Similar to any other matching strategy, we use some covariates to estimate the probability to be treated. Using this, we select two or three neighbors per unit treated to be part of the control group. we chose two or three being aware that it is really likely that one of the units matched for unit i, also can be a match for unit j. Then we estimate a common Difference in Difference for short and medium run impacts and for first, second and third neighbors. One of the question is why are we not using the Spatial Difference in Difference? Two are the reasons: given that the control groups is not longer a continuos geographic surface and just have random units selected within the city then a spatial model will not add significant information about neighbors or surrounding areas. The second reason is because we indeed are account for spatial relationship somehow. When we defined the treatment area as first or second or third neighborhoods, we assume that the impact of the Metrocable was not only on the area where it is located, but also in the nearby units.

Finally, Table 7 shows the results of this exercise. The first part of the table contains the results using the Max-p regions as the units of analysis, while the bottom panel of the table presents the results using neighborhoods. The results are considerable consistent across specifications and evidence that the Metrocable had a significant impact on those units treated respect to the control group. In fact, the results found in this robustness check are considerable greater in magnitude, showing that the impact overtakes the 50 percent. However, this is not surprising, as we have mentioned earlier the analysis made on an specific control group can be overestimated since it probably will not take into account the decreasing homicides trend in the city.

[11] Di Tella and Schargrodsky (2004) has 14 units treated and 53 control. Corsaro et al. (2012) has 122 treated, while the control group is composed by 1583 units. Similar, Benavente et al. (2011) used 12 and 84 treated and control units respectively.

Table 7—: Genetic Matching & Difference in Difference

Max-p regions as analytical units			
	1st Neighbors	**2nd Neighbors**	**3rd Neighbors**
Short impact (2004-2006)	−0.53	−0.53**	−0.41*
	(0.32)	(0.24)	(0.21)
	−41.21%	−41.28%	−33.61%
Medium impact (2004-2012)	−1.01***	−0.82***	−0.84***
	(0.30)	(0.24)	(0.20)
	−63.50%	−55.82%	−56.83%
Neighborhoods as analytical units			
	1st Neighbors	**2nd Neighbors**	**3rd Neighbors**
Short impact (2004-2006)	−0.25	−0.28	−0.18
	(0.26)	(0.23)	(0.23)
	−22.00%	−24.72%	−16.07%
Medium impact (2004-2012)	−0.55*	−0.83***	−0.69***
	(0.31)	(0.26)	(0.22)
	−42.55%	−56.39%	−49.75%

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages are calculated using the formula to approximate the marginal impact of a dummy in a log functional form. For the matching initial process, we include variables of slope and elevation of the units of analysis. As we expected, those variables are statistically significant to explain the probability of being treated. Results for all this process is available upon request.

Buffers

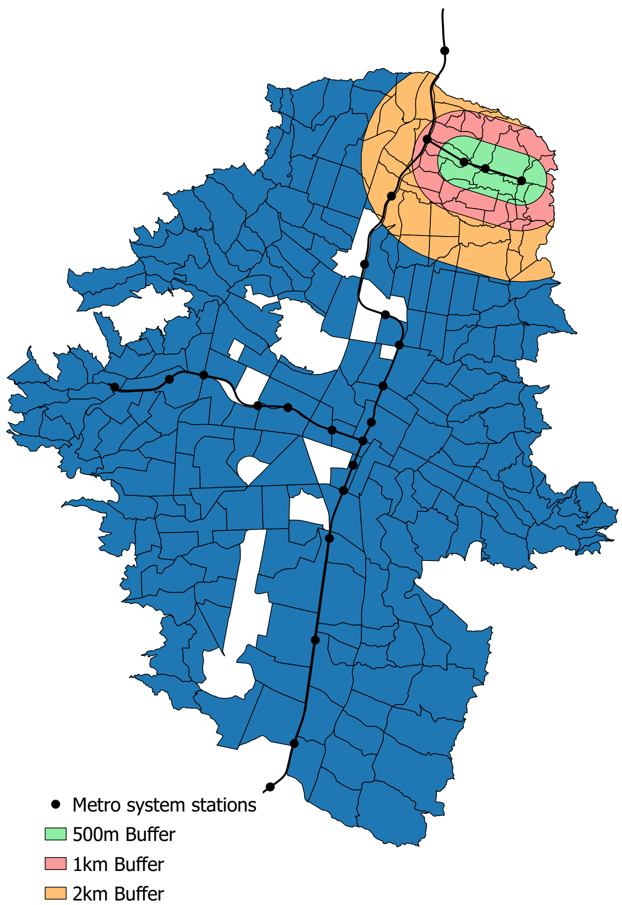
During all this analysis we have defined the spatial relationship across units as a contiguity process. That means, we are assuming that the spatial effect of the treatment of those units not treated is spread through the borders shared between geographical adjacent units. However, more other definitions can be used.

One of the most used options to define a spatial relationship is across metric distance. The thoughts behind that definition are based on the fact that two units can be spatially correlated if the distance between them is below an specific threshold. In the case of the influenced area of an intervention, we can assume that there is an effect over all that area within an specific threshold, assuming also that the effect in areas further than that threshold is equal or close to zero.

Thus, we define an influence area of 500 meters, 1 kilometer and 2 kilometer in which we assume the Metrocable had some impact. Table 8 shows the results of that exercise. The results for the impact in an area of 500 meters around the Metrocable are kind of similar to those that we found for treated units. This is because, as we have mentioned previously in this section, the treated neighbors are in an average distance close to 500 meters. The impact is much greater on the units until 1 kilometer apart than those units until 2 kilometer apart. In a 1 kilometer, the construction of the Metrocable decreased homicides in 49 percent more than the control group, while this figure is 43 for the buffer of 2 kilometers.

There estimated imopacts are really similar to the main results discussed, and they are a strong support of the strategy chose. The effect of the intervention on homicides is not driven by the particular structural definition of the spatial relationship rather that by the interactions within the influenced area.

Figure 5. : Buffers for Spatial Relationship



Source: author's calculation
Note: using the complete line of the Metrocable we draw a buffer around the area with radius 500 mt., 1 km. and 2km. We define as unit of analysis, those neighborhoods or maxp regions that had more of 10 percent of their area inscribed in the buffer.

VI. Discussion

This paper drives a research question that focuses on the relationship between urban public transportation investments and the evolution of crime. Public trans-

Table 8—: Buffer Treatment Assignment with Differences in Differences

Dependent: ln(Homicides+1)	500m	1km	2km
Short Impact (2004-2006)			
Total Impact	−0.29	−0.31*	−0.02
	(0.21)	(0.18)	(0.15)
	−24.83%	−26.58%	−2.41%
Net of Economic mechanism	−0.27	−0.28	−0.03
	(−0.20)	(0.17)	(0.15)
	−23.72%	−24.11%	−2.60%
Net of Police mechanism	−0.32*	−0.30*	−0.03
	(0.19)	(−0.16)	(0.14)
	−27.54%	−25.85%	−2.60%
Net of Both mechanisms	−0.21	−0.18	0.05
	(−0.20)	(−0.17)	(0.15)
	−19.26%	−16.15%	4.85%
Medium Impact (2004-2012)			
Total Impact	−0.42*	−0.67***	−0.55***
	(0.24)	(0.20)	(0.17)
	−34.48%	−48.76%	−42.54%
Net of Economic mechanism	−0.38	−0.66***	−0.57***
	(0.23)	(0.19)	(0.17)
	−31.72%	−48.08%	−43.48%
Net of Police mechanism	−0.42*	−0.57***	−0.47***
	(0.22)	(0.18)	(0.16)
	−34.34%	−43.72%	−37.49%
Net of Both mechanisms	−0.35	−0.53***	−0.45***
	(−0.22)	(0.18)	(0.16)
	−29.71%	−41.31%	−36.29%

Source: author's calculation
Note:*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Percentages are calculated using the formula to approximate the marginal impact of a dummy in a log functional form. To obtain the impact of each mechanism as a percentage of the total impact, the result from the net of mechanism's coefficient over the total impact's coefficient should be subtracted from 1 and then multiply per 100.

portation is seen by some as a source of security zones and by others as crime attractors. Either situation can arise as a result of urban planning and public policy design.

The new public transportation facilities opened in 2004 in Medellin, Colombia, that consist of a gondola system called Metrocable is one good example of a new and different way to integrate particular areas of the city characterized by difficult geographic conditions into the public transportation system. How such facilities are designed determines the indirect impact that such an intervention will have on other socioeconomic variables. Facilities can be a source of security if the probability that criminals will be apprehended increases with their release, or if the perception of policing is greater in those areas where the new facilities are located.

Estimation results using a Spatial Difference-in-Difference approach suggest that the Metrocable had a large and significant impact on reducing homicides.

In summary, those neighborhoods where the Metrocable is located decreased the level of monthly homicides an average of 49% more than the generalized homicide decrease experienced by all neighborhoods of the city. Even more impressive, strong evidence exists that the indirect treatment effect on non-treated units is not zero.

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Appendix 1: Endogeneity of captures

In order to measure the police mechanism related to the fact that more police presence increases the probability of apprehension and then deterring crime; we used captures as a proxy. However, in this context where we have more than 1 period of time we face a problem of possible endogeneity across that variables: captures and homicides. More captures deters crime, but there would not be a capture if homicides had not happened. To address this problem we take advantage of the extremely disaggregated information we have for captures. We are able to identify the type of captures: if they were for homicides, drug's related crimes, extortion, sex-violence and many other more. We use a simple strategy to test how concern we should be about this problem. To do that, we apply a similar strategy to the Granger causality and dynamic panels. The following equation summarizes all the strategy used:

$$Hom_{i,t} = \alpha_0 + \sum_{j=1}^{p} \rho_j Hom_{i,t-j} + \sum_{m=0}^{q} \beta_m Cap_{i,t-m}^{(k)} + u_{i,t} \tag{A1}$$

To cover all the options possible and to address the main concern issue, we have two variations of i (units of analysis: neighborhoods and max-p regions) and two variations of t (time: annual and quarterly). For the yearly specification we have information from 2004-2014, and the values of p and q are both equal to 2 (2 years lags). Let us clarify that p represents the number of homicides lags using in the right hand and the q is the number of captures lags used also as controls. However, for the quarterly specifications, we used $p = 7$ and $q = 11$. Those figures are given by the number of quarters included in the first yearly scenario.

The logic here is fairly simple. The reason why we include the homicides lag is because we are dealing with a dynamic panel, so the homicides history should matter. Then, if the endogeneity between captures and homicides exists, using the captures lags as instrumental variables, it will make that the captures lags are statistically significant to explain homicides i.e. the joint t-test on the β_m will be different to zero and the p-value will be below the common confidence level (10%). In order to test this, we use different definitions of captures ($Cap^{(k)}$, where $K = 1, 2, ..., 6$) which are defined in Table A1.

Summarizing this strategy, Figure A1 displays the p-value corresponding to the joint t-test on the statistical significance of β_m for each of the 4 variations (each variation per line) and for each of the capture variables (each capture in the X axis). This figure states that from the moment we stop excluding the captures related to drugs ($Cap^{(5)}$) the join t-test fell in the rejection zone, meaning that the captures lags indeed are significant to explain homicides, presenting some evidence about endogeneity. But, for $Cap^{(1)}$ until $Cap^{(4)}$ the figure does not show any strong evidence of endogeneity presence among those captures definition. We, in our paper, used $Cap^{(2)}$ as the proxy for the police mechanism.

Table A1—: Specification of capture variables

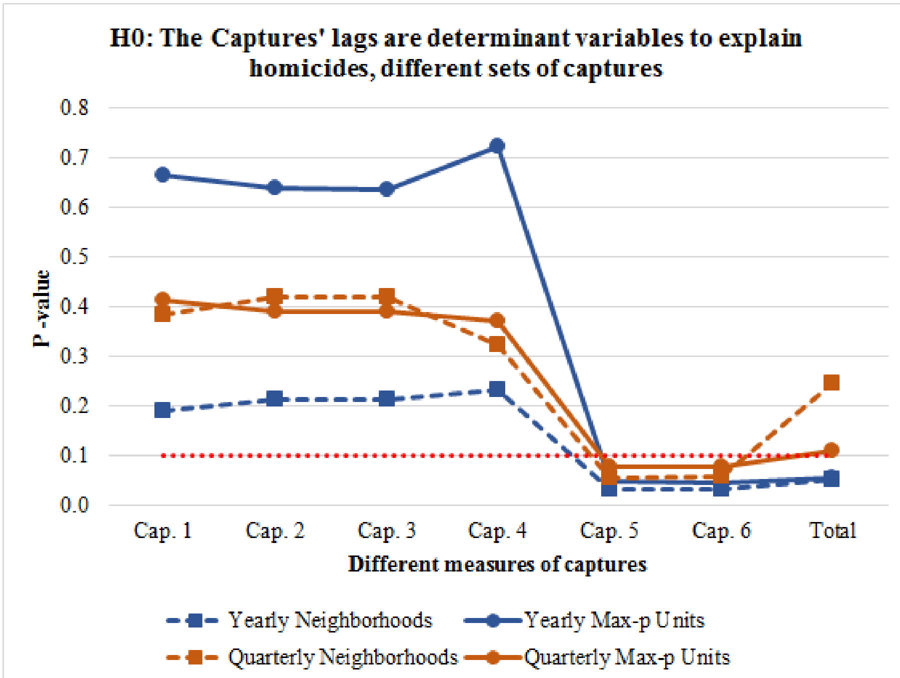
Capture variable	**Excluded types of captures**
$Cap^{(1)}$	**Kidnapping**, illegal recruitment, terrorism, drug-related, manslaughter and homicide
$Cap^{(2)}$	**Illegal recruitment**, terrorism, drugs-related, manslaughter and homicide
$Cap^{(3)}$	**Terrorism**, drugs-related, manslaughter and homicide
$Cap^{(4)}$	**Drug-related crimes**, manslaughter and homicide
$Cap^{(5)}$	**Manslaughter** and homicide
$Cap^{(6)}$	**Homicide**
Total	**Any** capture excluded

Source: author's calculation
Note: the grouping of the captures for each definition were made according to the Medellin special case. First, we drop strictly homicides, then all drug related crimes, and then all crimes related to illegal armed groups.

Appendix 2: Monthly structure

One of the things that our database allows us to do is running some models on a monthly structure. Although, we cannot have any particular covariate for this exercise we will include month year fixed effects in order to account for all specific events during that period. We will use also a similar estimation strategy

Figure A1. : Endogeneity test for different captures measurements



Source: author's calculation
Note: since we are focusin on homicides and captures only, the orange lines represent the quarterly models while the blue lines are the yearly. The red dotted line on 0,1 P-value represent the standarize threshold for null hypothesis's rejection. The main models used Cap. 2, but as it shows Cap. 1 trought Cap. 4 work.

that the main estimation had. We divide the impact in the direct effect (effect of treatment on treated) and the indirect or spatial component (effect on those close to the treated but they were not treated). It is important to mention that this monthly structure can identify temporal variations or shocks in the outcome variable that can be explained by the treatment, but in this case the strategy will not strongly identify structural relationships.

Table B1 presents the results of a model where the log of homicides in the neighborhood i is the dependent variable, and it is a function of the homicides in its neighbors (rho), if it has been treated and if its neighbors also were treated. The inclusion of the neighbors follows the structure stated by Anselin and Smirnov (1996), who argue that using the contiguity matrix is is possible to build a matrix which contains greater spatial lags, meaning matrices that can identify the second degree neighbors (neighbors of neighbors) until umpteenth degree neighbors. The first panel of the table "Model Treatment" contains that results. In this case, the impact is negative for both direct and indirect effect, but it is the indirect effect which is statistically significant. This is exactly what we have seen before, due to the reduce number of neighborhoods treated there is not enough statistical power to check the significance of the direct impact, however, the indirect impact which accounts for first, second and third neighbors shows a significant decrease of homicides. This analysis is done for the period 2003-2006, and the treatment variable is equals one for all the periods after the intervention: 2004 month 7.

The following three panels contains also the direct, indirect and total impact of the treatment, but we break down the treatment variable per periods. This will lead us identify the exact period of time when the intervention had a significant impact. The relevant periods for us are 6 months exposed to the treatment ($t_0 - t_5$), between 6 and 12 months of the treatment ($t_6 - t_{11}$) and between 12 and 18 months ($t_{12} - t_{17}$). Also, we want to corroborate if there is any particular effect driving the results prior the intervention, to achieve that we added a variable of treatment equals one for 6 months prior the Metrocable construction (t_{-6}). First, in all the cases this last variable was not significant, as an evidence that there was not pretrend effects driving the results we have found through this study.

For the direct impact, the treatment shows some effect after 6 months of the intervention. This means that those neighborhoods where the Metrocable is located starting to experience reductions in homicides greater than the rest of the city between six months and 1 year of the construction. However, the indirect impact started 6 months later. Those neighborhoods near the metrocable experimented greater reductions of homicides after more than 1 year of the construction.These figures sustain our hypothesis and the results discussed in the paper, the impact of an intervention is spreading through the neighborhoods if there is indeed a spatial link between them; and it is just until 2006 where the intervention starts to point out its impact.

Appendix 3: Placebo test

To identify the impact that a new public transportation intervention had on crime, this study will conclude with what it is commonly called as "placebo" test. Under this circumstances, we have been showing some satisfactory results about the intervention of the Metrocable and its significant impact on the decreasing of homicides in the area treated and the surrounding zones. we want also to show that the results obstained are not driven for a general reduction pattern of homicides in the city, neither they are confounded significantly for another public interventions. In order to do that, we define a "placebo" Metrocable or a fake Metrocable.

Figure C1 shows in a light green dots the stations of our fake Metrocable. We tried as much as possible that the Metrocable fitted in an area with similar characteristics, specifically slope and elevation, to the one where it was really built. Also, the length of the fake Metrocable is the same that the real one, and the distance between stations remain unchanged. Similar to what we did to estimate the impact of the real Metrocable, we define the units treated as those

Table B1—: Direct, Indirect and Total impact of Spatial Model

	$1stNeighbors$	$2ndNeighbors$	$3rdNeighbors$
Model Treatment			
Direct	-0.06	-0.16	-0.20 *
	(0.16)	(0.11)	(0.11)
Indirect	-0.43 *	-0.53 ***	-0.68 ***
	(0.24)	(0.16)	(0.23)
Total	-0.50 ***	-0.68 ***	-0.89 ***
	(0.16)	(0.17)	(0.24)
rho	0.04 ***	0.11 ***	0.14 ***
	(0.01)	(0.02)	(0.03)
Direct			
Treatment($t_0 - t_5$)	-0.06	-0.07	-0.08
	(0.09)	(0.06)	(0.05)
Treatment($t_6 - t_{11}$)	-0.15	-0.13 ***	-0.15 ***
	(0.11)	(0.05)	(0.04)
Treatment($t_{12} - t_{17}$)	-0.05	-0.10	-0.14
	(0.11)	(0.09)	(0.08)
Treatment(t_{-6})	-0.14	-0.11	-0.10
	(0.10)	(0.08)	(0.07)
Indirect			
Treatment($t_0 - t_5$)	-0.08	-0.11	-0.12
	(0.14)	(0.17)	(0.22)
Treatment($t_6 - t_{11}$)	-0.05	-0.22	-0.35 **
	(0.20)	(0.15)	(0.17)
Treatment($t_{12} - t_{17}$)	-0.25 **	-0.32 ***	-0.36 *
	(0.12)	(0.12)	(0.19)
Treatment(t_{-6})	0.09	0.02	0.01
	(0.12)	(0.17)	(0.22)
Total			
Treatment($t_0 - t_5$)	-0.14 *	-0.18	-0.21
	(0.08)	(0.13)	(0.20)
Treatment($t_6 - t_{11}$)	-0.21 *	-0.35 ***	-0.49 ***
	(0.12)	(0.14)	(0.16)
Treatment($t_{12} - t_{17}$)	-0.30 ***	-0.42 ***	-0.50 ***
	(0.10)	(0.12)	(0.19)
Treatment(t_{-6})	-0.06	-0.09	-0.09
	(0.08)	(0.14)	(0.21)
rho	0.05 ***	0.14 ***	0.20 ***
	(0.01)	(0.02)	(0.04)

Source: Authors calculation.
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. These models include time fixed effects and neighborhoods fixed effects. Errors are clustered at neighborhood level and normalized contiguity matrices were used for all models. The first column shows the results using the standard contiguity matrix W, the second results column presents the case using the second degree of contiguity and the third column is just the third degree of contiguity. The first panel of the results called Model treatment refers to the results when the treatment variable has not been broken down by time periods yet.

where the Metrocable is located, any facility. Then we identify their first, second and third neighbors.

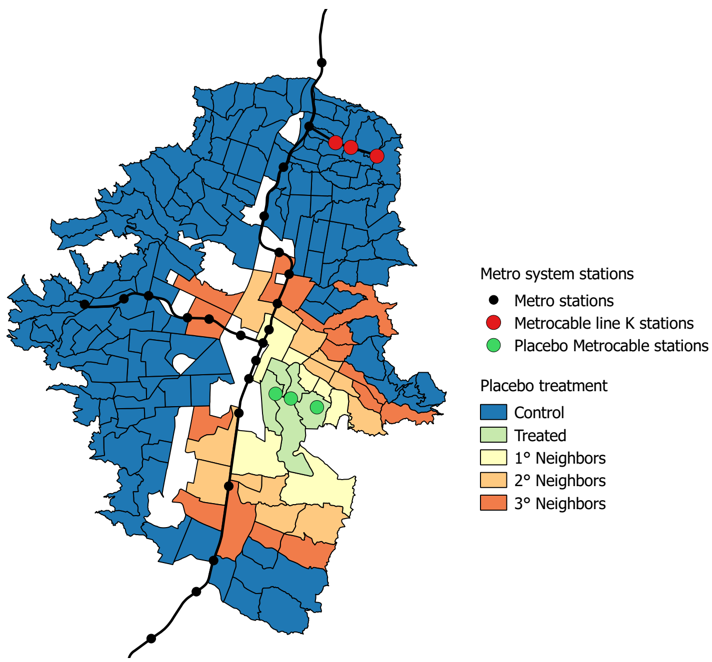
Finally, we run the main model using this fake Metrocable as the intervention. What could we expect? If the Metrocable is a real deterrent of crime we should not see some impact in this exercise. In opposite way, if we find some significant impact, the impact of the Metrocable identified previously contains effects coming from another sources different to the intervention. Table C1 shows the principal results for the placebo test, both common and Spatial Difference in Difference, and also for the short and medium run for treated, first, second and third neighbors. As we can infer, there is not strong evidence that the fake Metrocable will be responsible of the variations in homicides in that area of the city.

Table C1—: Placebo test. Conducted by creating a fake Metrocable line over Buenos Aires & La candelaria.

Dependent: ln(Homicides+1)	**Treated**	**Treated + 1st Neighbors**	**Treated + 2nd Neighbors**	**Treated + 3rd Neighbors**
Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	-0.50	-0.16	-0.12	-0.20
	(.4 023 196)	(.3 714 238)	(.2 687 632)	(.2 093 324)
		Medium Impact (2004-2012)		
Total Impact	-0.64**	-0.41	-0.29	-0.18
	(.3 193 779)	(.3 180 814)	(.2 475 541)	(.1 913 972)
Spatial Difference in Difference				
		Short Impact (2004-2006)		
Total Impact	-0.54	-0.17	-0.13	-0.20
	(.4 385 539)	(.2 911 712)	(.2 142 579)	(.1 808 613)
		Medium Impact (2004-2012)		
Total Impact	-0.62	-0.43	-0.32	-0.20
	(.4 476 387)	(.2 944 764)	(.2 236 706)	(.1 869 958)
Number of treated units	5	12	24	39
Number of control units	171	164	152	137

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The place for the fake Metrocable was chosen according to the terrains' slope, it is similar to the slope of the real Metrocable. Also, the distance between stations is the same than in the real one, as well as the complete length of the Metrocable.

Figure C1. : Placebo treatment assignment



Source: author's calculation
Note: the place for the fake Metrocable was chosen according to the terrains' slope, it is similar to the slope of the real Metrocable. Also, the distance between stations is the same than in the real one, as well as the complete length of the Metrocable.