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

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Abstract

In 2004, the Colombian city of Medellin completed the construction of a public transportation system based on cable cars (Metrocable) that reached isolated dense neighborhoods. Using spatial difference in differences, a mechanism estimation strategy, and a rich, spatially disaggregated dataset, we explore the effects of the Metrocable on crime and its mechanisms. We find a significant impact on homicide reduction in the treated and adjacent neighborhoods, especially in the medium run. The decrease in homicides was approximately 40 percent greater than the reduction in the general crime rate in the city between 2004 and 2006 and 51 percent between 2004 and 2012. We explore two mechanisms through which this intervention may affect the level of criminality – the inclusion mechanism and the deterrence mechanism – and find significant results that account for more than one-third of the effect in the short run.

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

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1 Introduction

The provision of public transportation infrastructure is an important tool for improving the quality of life and promoting growth in urban settings (Munnell, 1992; Sanchez-Robles, 1998; Holtz-Eakin and Schwartz, 1995). Population growth, the layout of the city, and geographical characteristics can limit residents' mobility and integration into the urban economy, and thus a variety of innovative transportation systems are necessary to accomplish these policy objectives. Over the past few years, cable cars have emerged as a new for transportation in the developing world, due to their relative low cost and ability to access remote, deprived, and often dangerous neighborhoods.

Unfortunately, there is little empirical evidence on the direct effects of this type of infrastructure and even less on its unintended effects, such as either the increase or reduction of criminality in surrounding areas. The implications of cable car interventions with regard to crime are of particular interest, given that cable cars are usually used to reach isolated neighborhoods that are typically underpoliced and suffer from relatively high crime rates.

The empirical evidence on the link between public transportation infrastructure and crime is limited and has been generated by investigations in developed countries. On the one hand, a handful of studies on US cities argue that train stations act as crime attractors that create concentrations of citizens and consequently well-known opportunities for particular types of crime, thereby increasing the probability of crime (Levine and Wachs, 1986; Brantingham and Brantingham, 1993; Loukaitou-Sideris, 1999). On the other hand, a group of studies shows that the design of stations and their surroundings (lighting, surveillance systems, tree and vegetation placement, etc.) plays an important role in the levels of fear related to crime and crime rates, leading to the conclusion that proper design may reduce crime rates (La Vigne, 1996; Cozens et al., 2003). Moreover, as argued by Foster et al. (2010) the spatial correlation between adjacent neighborhoods may factor significantly in this relationship. From a security perspective public transportation may reduce the fear of crime for those living close to a station, as citizens feel safer when they trust that neighborhood acquaintances are monitoring their actions and will provide help if criminal activity occurs.

The city of Medellin, Colombia, presents a unique framework for the study of the relationship between public transportation infrastructure and crime. Just a couple of decades ago, Medellin was considered one of the most unequal and violent cities in the world (Giraldo Ramírez, 2010). However, the city has shown a remarkable reduction in crime rates, with the average annual homicide rate dropping from 381 homicides per 100,000 inhabitants in the early 1990s to 98.2 in 2003 and 26.95 in 2014. Following major military operations, such as the one that ended the Medellin drug cartel in 1993 and the Orion Operation that retook control of the western part of the city in 2002, local authorities implemented innovative initiatives to deal with the problems that arise when a city's growth exceeds the capacity of local authorities to deliver services and infrastructure (Ibáñez and Vélez, 2008; Patiño et al., 2014).

These initiatives sought to impact mobility and economic integration simultaneously. One of the most important investments during this period was in the construction of a cable car (Metrocable) line at the end of 2004, which connected one of the most isolated and far-flung neighborhoods in the northeastern hills of the city (with slopes steeper than 20 percent) to the Medellin Metro System. The Metrocable reduced commute time from 2.5 hours to 7 minutes (United Nations, 2007). This investment was multidimensional: it provided a new transportation system, but also transformed the neighborhoods' physical environment. Significant investment in sidewalks, street improvement, and air quality around the Metrocable infrastructure complemented the system.

Given the vast evidence on the relationship between public transportation infrastructure and its surroundings and crime, the construction of a cable car line connecting the central business district (CBD) with peripheral, isolated (due to topography), and low-income neighborhoods in one of the most violent and unequal cities in the world makes this urban intervention a fascinating case study. Surprisingly, to the best of our knowledge, since the construction of this infrastructure in 2004, only one case study has been published in a peer-reviewed scientific journal. Cerda et al. (2012) estimated that due to the intervention neighborhoods experienced a drop of 66 percent in homicide rates. However, as the authors acknowledged, their study was not designed to investigate the mechanisms that produced the observed drops in violence. Additionally, the authors disregarded the potential spatial spillovers of this infrastructure by assuming that the effect of crime reduction was limited to the neighborhoods served by the transportation system.

Using a rich crime and socioeconomic dataset and quasi-experimental methods, we reexamine the effect of the cable car system in Medellin on crime, specifically homicide. Furthermore, no previous study has considered the spatial nature of such an intervention, which implies that the presence of new transport infrastructure affects not only the areas where the infrastructure is physically located, but also, via spillovers or indirect spatial effects, adjacent areas (Foster et al., 2010). Finally, we explore how the Metrocable affects homicide rates and argue for the existence of two main mechanisms in this regard. First, this new public transportation system increases people's accessibility to more economic opportunities and amenities, which can play an important role in reducing criminal activities. This mechanism is related to the spatial mismatch theory first proposed by Kain (1968), which states that opportunities for low-income people are inaccessible, because of where they live.[1] Second, the presence of new public infrastructure usually increases the level of surveillance, thereby increasing the probability of apprehension, which serves 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 the space and time of an offender, a target, and the absence of surveillance.

Thus, this paper contributes to the current literature in at least two ways. First, we propose a way to estimate the impact of treatment effects and their mechanisms when the treatment is particularly related to a geographical intervention. To this end, we extend the literature on spatial treatment effects to include a method of examining mechanisms in spatial difference-in-differences models (SDiD). The second contribution is a precise estimation, based on these methods, of the effects of infrastructure on crime.

The remainder of this paper is organized as follows: The second section presents the empirical strategy used in the paper. The third section describes the datasets used, and the fourth section presents our results. Finally, the fifth section provides a discussion of this analysis.

2 Empirical Strategy

The Metrocable was intended to increase the accessibility levels of people living in areas of Medellin remote from the conventional metro system. This geographically based location

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

process resulted in a nonrandom assignment of treatment and control units, causing a selection bias that must be addressed. In addition, due to the characteristics of the intervention and the available data, there exist a number of unobservables that could potentially affect the estimates. Therefore, we applied a difference-in-differences approach to identify the impact of the intervention. However, the observed spatiotemporal patterns show that areas close to the treated neighborhoods initially behaved like the rest of the city but, after a certain amount of time, began to converge toward the behavior of the treated regions, which poses an additional challenge. To overcome these problems, we propose a spatial difference-in-difference (SDiD) approach similar to those of Delgado and Florax (2015) and Chagas et al. (2016) that allows for the inclusion of a component to capture the indirect treatment effect on nearby nontreated regions. Given their proximity to the treated regions, if the intervention is really a crime deterrent, the indirect treatment effect on the nontreated regions should exist and be negative.[2]

These indirect effects, also known as spillover effects, are relevant for this empirical exercise. First of all, geographic divisions although in place are not as visible as those between cities or countries. While delimiting a treated region means that in theory the geographical extent of the spread of the treatment effect is known, at minimum the closest neighborhoods may need to be included in order to test whether the effect is actually bounded by those locations. Second, crime has a spatial component that is not new to the literature or the empirical exercise (see Urrego et al., 2016). High-crime neighborhoods tend to be surrounded by high-crime neighborhoods, a pattern that is related to socioeconomic variables at the neighborhood level, such as income, schooling, and quality of life. Recall that in the routine crime models an offense needs an opportunity, a potential target, and an offender; either a victim or a perpetrator of a violent event can come from neighboring regions and the spatial correlation between those neighborhoods could account for the spillover effect deriving from their proximity to each other. Following Delgado and Florax (2015), we depart from the standard difference-in-differences

[2]The estimation method provides additional value through the consideration of spatial effects by taking into account the spatial distribution of the regions. This approach has profound implications on the area of influence of the intervention. In a nonspatial approach, this area of influence is defined a priori, whereas in a spatial approach, the area of influence is endogenously defined by considering the spillover effects (both direct and indirect) between regions. The spatial approach also allows for asymmetrical impacts (e.g., the intervention may be beneficial for a set of regions and harmful for other regions). Finally, this approach enables the differentiation between the portion of the effect produced by the treatment and the portion resulting from the spatial linkages across regions.

structure:

$$Y_{it} = X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t + \alpha D_i * t_t + U_{it} \tag{1}$$

Where, Y_{it} represents the crime outcome of regions, i represents the index for regions, and t is an index for the time periods. As in Rubin (2005), we henceforth refer to the potential outcomes of the treatment and the control group as $Y(1)$ and $Y(0)$, respectively. X_{it} is a vector of observed time-varying covariates. D_i is a dummy variable equal to 1 if region i was treated and equal to 0 otherwise. t_t is a time dummy equal to 1 for the year after the treatment and equal to 0 for the year prior to the treatment. The parameter α identifies the impact of the treatment, and U_{it} is a mean-zero error term that is uncorrelated with D_i and t_t. Adding the spatial component to Eq. (1) gives us Eq. (2):

$$Y_{it} = \rho W_i Y_t + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t + \alpha D_i * t_t + \alpha_2 W_i D + \delta W_i D * t_t + U_{it} \tag{2}$$

where, W_i corresponds to the row i of the square matrix W, which refers to the spatial weight matrix. W is a row-standarized spatial weight matrix of dimensions $N \times N$, with N representing the number of regions. The nonzero elements in W indicate the existence of a spatial neighboring relationship between regions. One can express the Eq. (2) in matrix form, staking the two periods considered for analysis (before and after treatment); in such a case the spatial weight matrix W will be of dimension $2N \times 2N$. In this 2×2 block matrix the top-left block represents the spatial relationship between regions in the time before treatment, the bottom-right block captures the spatial relationship between regions after treatment, the top-right captures the spatial relationship across regions and across time, and a similar meaning is embedded in the bottom-left block. These two last blocks are assumed to be zero; in the empirical setting this implies that neighborhoods today are spatially correlated with other neighborhoods today, but the correlation with other neighborhoods and itself is discarded in future periods.

Observe that this assumption only rules out direct correlation between a neighborhood and others across periods coming from the spatial matrix, which in our case is defined based on geographical location. Therefore, allowing such a direct link between neighborhoods across time does not add much to the exercise, since the correlation specified using geographical distance is constant across time. Our final block matrix W, then, has two submatrices different from zero and located on the main block diagonal. According to the definition of W by Delgado and Florax (2015), each submatrix can have a different neighboring relationship; in our case the two submatrices are equal, since they are constructed using neighborhood location.[3]

The right-hand side of Eq. (2) combines scalars and vectors, Y_t and D being vectors $N \times 1$ that collect all the values for the regions at a given time t. ρ is a spatial autocorrelation parameter. Building on the formulation proposed by Delgado and Florax (2015), our expression contains two spatial terms related to the treatment: α_2 accounts for the spatial autocorrelation between a region and the rest of the regions, and δ, a spatial impact $W_i D = wd$, accounts for the impact of the treatment on regions that were not treated but are spatially correlated with the treated regions. In other words, observe that wd can be different from zero even though $D_i = 0$, because the region i is spatially correlated with other regions that may be treated. The spatial impact is defined under the realized spatial correlation coming from the *apriori* definition of the matrix W, so that the average treatment effect (ATE) also should be understood as conditional on the realized spatial correlation.[4]

From Eq. (2), we can derive the conditional ATE as follows:

$$\begin{aligned} ATE(wd) =& [\ E(Y \mid X,\ D=1,\ t=1, WD=wd) \\ & - E(Y \mid X,\ D=1,\ t=0, WD=wd)\ ] \\ & - [\ E(Y \mid X,\ D=0,\ t=1, WD=0) \\ & - E(Y \mid X,\ D=0,\ t=0, WD=0)\ ] \end{aligned} \tag{3}$$

Before identifying the corresponding values, we should note that our specification also contains a spatial autoregressive term, so without losing generality, we can restructure any coefficient as $\alpha^{'} = \alpha * (I - \rho W)^{-1}$ (assuming that $I - \rho W$ is nonsingular).

$$ATE(wd) = \left[\alpha_0^{'} + \alpha_1^{'} + \alpha^{'} + \alpha_2^{'} + \delta^{'} wd - \alpha_0^{'} - \alpha_2^{'}\right] - \left[\alpha_1^{'}\right] = \alpha^{'} + \delta^{'} wd \tag{4}$$

[3]See Dubé et al. (2014) for a detailed explanation on building spatiotemporal weight matrices.

[4]There are other options for the matrix W, but it should be kept in mind that since the unit of analysis is geographic and small, using socioeconomic variables to define W can be difficult, due to the process of data aggregation and the clear delimitation of each area. Matrices using geographic information seem appropriate, however; the location remains fixed over time, so that one can see wd as the realized location itself rather than as a specific spatial matrix for the scope of this section.

We can rewrite this based on the possible set of spatial impacts of the treatment and show the similitude to the exercise by Delgado and Florax (2015):

$$ATE(wd) = \alpha^{'}\left(I + \delta^{'}wd\right) \rightarrow ATE = E\left[ATE\left(wd\right) \mid WD\right] = \alpha^{'}(I + \delta\overline{WD}) \qquad (5)$$

Our treatment impact will thus be the following:

$$ATE = \alpha(I - \rho W)^{-1}\left(I + \delta\overline{WD}\right) \qquad (6)$$

In the next step, which presents one of this paper's important methodological contributions, we proceed to formulate the decomposition of ATE within the context of an SDiD into two effects: a causal mechanism, or indirect effect, and a causal net, or direct effect. This formulation enables us to understand the roles of the two proposed mechanisms, namely, labor market outcomes (wages, informality) and the apprehension mechanism. In the empirical framework, the indirect effect refers to the impact that the construction of the Metrocable has on the level of crime through the impact that the Metrocable has on the local labor markets and felons apprehensions, which we will refer to now on as the two mechanisms. We focus on these two due to the nature of the intervention, which we discuss in the next section. The labor mechanism focuses on the impact that the new transportation system has on commuting time, cost of transportation, and access to labor markets. The apprehension mechanism refers to the fact that when the system stations were being built, security cameras were installed, and once the system began to operate local police were assigned to the stations, which contributed to better police enforcement. The direct effect refers to the impact of the Metrocable that does not come from the two mechanisms just discussed; strictly speaking, it compiles all other mechanisms not accounted for in the variables we include to identify the labor and apprehension mechanisms (it is indicated by the other name for this impact: the causal net effect).

For that purpose, and based on the methodology presented by Flores and Flores-Lagunes (2009), we define a variable S_j that represents the mechanism j through which the intervention could affect the outcome. $S_j\left(1\right)$ represents the value of the mechanism j if the region is treated, and $S_j\left(0\right)$ represents the value of the mechanism if that region is not affected by the treatment. Thus, with this new variable we can define four potential outcomes: $Y(1,\ S_j(1))$, the potential outcome of those that were treated, if the mechanism j is affected by the treatment; $Y(0,\ S_j(0))$ the potential outcome of the control group, if the mechanism is not affected by the treatment; $Y(1,\ S_j(0))$, the potential outcome of those that were treated, if the treatment does not affect the mechanism; and $Y(0,\ S_j(1)) = 0$, the potential outcome of the control group, if the mechanism has been affected by the treatment. Similar to Flores and Flores-Lagunes (2009), we do not consider this last potential outcome, since in our empirical framework it is not particularly relevant. It implies that regions far from the Metrocable area would have benefited from improved employment conditions and more effective policing resulting from the construction of the Metrocable, a very unlikely scenario. Labor market improvements tend to be local, because it is not efficient for a person in another area to travel to the treatment area in order to benefit from the Metrocable. Similarly, police presence is extremely localized, as policemen assigned to the Metrocable stations must remain in the immediate vicinity.

Based on Frangakis and Rubin (2002), we redefine the ATE conditioning on the specific group observed for each potential mechanism outcome $\{S_j(0) = s_{j0},\ S_j(1) = s_{j1}\}$. Simplifying Eq.(3), we rewrite it leaving out the index j, since the definition applies to all j:

$$\begin{aligned} ATE =& E[E[Y(1, S(1))\,|X, D, t, W, S(0) = s_0,\ S(1) = s_1] \\ & - E[Y(0, S(0))\,|X, D, t, W, S(0) = s_0,\ S(1) = s_1]] \\ =& E[E[Y(1, S(1)) - Y(0, S(0))\,| \\ & X, D, t, W, S(0) = s_0,\ S(1) = s_1]] \end{aligned} \tag{7}$$

To identify the relevance of a mechanism, we rewrite the latest equation as follows:

$$\begin{aligned} ATE =& E[E[Y(1,\ S(1)) - Y(1, S(0)) + Y(1, S(0)) - Y(0, S(0))\ | \\ & X, D, t, WD, S(0) = s_0,\ S(1) = s_1]] \\ =& E[E[Y(1,\ S(1)) - Y(1, S(0))\ \mid X, D, t, WD, S(0) = s_0,\ S(1) = s_1]] \\ & + E[E[Y(1, S(0)) - Y(0, S(0))\ \mid X, D, t, WD, S(0) = s_0,\ S(1) = s_1]] \end{aligned} \tag{8}$$

The first term in the second equality of Eq. (8) estimates the component of the ATE that is due to a mechanism being affected by the treatment, $S(1)$, or the mechanism average treatment effect ($MATE$), and it applies for all mechanisms j. This component provides evidence of the impact of the treatment on the outcome variable through the mechanism j. Note that if the intervention did not operate through the mechanism, then $S(1) = S(0)$, and the first term will be zero. The second term of Eq. (8) estimates the difference in the potential outcomes of the treatment and control groups, constituting the effect of the treatment on the outcome that is not associated with a mechanism. We call this component the net average treatment effect ($NATE$). Thus, the ATE can be defined as $ATE = MATE + NATE$.

The challenge in estimating these expressions is that $Y(1, S_j(0))$ is not observable. We must design a strategy to estimate the potential outcome for the treated regions if the mechanism j is not affected by the treatment ($NATE$). To address this issue, we assume (1) that the assignment of the treatment is independent of the potential outcomes given a set of covariates X, and (2) that the potential outcomes are also independent of the possible values of the variables of the mechanisms (this is related to Assumptions 1 and 2 in Flores and Flores-Lagunes, 2009).

$$Y\left(1, S_j\left(1\right)\right), Y\left(0, S_j\left(0\right)\right), Y\left(1, S_j\left(0\right)\right) \ \perp D|\ X, t, W \tag{9}$$

$$Y\left(1, S_j\left(1\right)\right), Y\left(0, S_j\left(0\right)\right), Y\left(1, S_j\left(0\right)\right) \ \perp \ \left\{S_j\left(1\right), S_j\left(0\right)\right\} \ | \ X, t, W \tag{10}$$

The first difference between these assumptions and those in Flores and Flores-Lagunes (2009) is that we also condition for the realized spillover relationship embedded in the matrix W. Recalling the previous discussion about how W is defined in the empirical context, using geographical distance to structure the spatial correlation seems appropriate since our unit of analysis is region. Hence, W is assumed to be exogenous. In order to weaken this assumption, one can iterate over different known forms of W and observe how the results change. However, conducting that exercise is beyond the scope of the paper, since doing so will shift the question toward how to choose W, instead of toward how it is possible, given W, to estimate an ATE.

Similar to those in Flores and Flores-Lagunes (2009), the first assumption refers to the conditional independence of the potential outcomes with respect to the treatment. In our setting, this means that the potential outcomes related to the level of crime in the neighborhood do not depend on whether the neighborhood is in the treatment or control group after conditioning on the set of variables X. The location of the Metrocable followed on the geographical conditions of the neighborhoods and the lack of accessibility, variables that will be included, so the assumption is not undermined by variables that both define the treatment and are also related to crime. Some unobserved variables, confounders, can play important roles: for example, one could argue that extremely localized human behavior in the area behavior in the area reduces accessibility to the Metro system in ways different to location (e.g., the shape of the street network) making the area more likely to receive the treatment, as well as being more prone to higher crime rates. Although this is unlikely to be an issue for the assumption in Eq. (9), it is a point of concern in relation to the assumption in Eq. (10).

The assumption in Eq. (10) adds the additional layer of the potential outcomes being independent of the potential values of the mechanism due to the treatment. To understand what is behind this assumption, first recall that those regions where $D = 0$ has only one option for the mechanism variable $S_j(0)$; this additional layer thus focuses more on the potential outcomes for those in the treatment group. For the empirical exercise, this means that there are no other variables that are correlated with both the identified mechanisms (labor outcomes and police) and the potential outcomes. To better understand the implications of this assumption for the empirical exercise, consider the following example of variables that can undermine the independence assumption. There was a significant police intervention in 2002 (Operation *Orion*) where over the course of a couple of days the police and the army entered some isolated neighborhoods in significant numbers in order to capture criminals and regain control. Events like this will clearly be related to both the potential level of crime and the mechanism related to apprehension. However, this particular event does not have a significant impact upon our estimation, since it happened two years before the Metrocable intervention.

This exemplifies the type of confounders that may undermine the assumption in (10), that variables are localized in specific areas and correlated with the outcomes and the mechanisms. During the years covered by this analysis, the local government indeed invested in many public interventions around the city, but none of them have been as localized and therefore effective as the Metrocable. The next section will cover some of these public policy initiatives; it is relevant to mention here that they are in most cases at the city level. Some localized interventions, such as the construction of public libraries, were implemented around the city, such that the distance between a neighborhood and the closest public library decreased in most, if not all, instances, an outcome similar to that of the introduction of the Metrocable. For that situation, one can still argue that Eq. (10) holds.

After setting the baseline for the SDiD approach, we can return to the functional form considered for the spatial model at hand, Eq. (2). Translating this structure toward the previously defined potential outcomes, one can define the expected values in terms of a functional form for both, $Y(1, S_j(1))$ and $Y(0, S_j(0))$:

$$E\left[Y\left(1, S_j\left(1\right)\right) \mid S_j\left(1\right) = s_{j1},\ X, t, W\right] = f_1\left(S_j\left(1\right), X, t, W\right) \tag{11}$$

In the functional form $f_1(\cdot)$, the subindex 1 refers to the treatment group—in other words, the functional form is assumed to be unique for the treated regions and takes the potential value of the mechanism and the matrices X and W as exogenous. It is possible to define another functional form to address whether the mechanism is affected or not; however, in this scenario that option is not worth pursuing. Consider the example of the apprehension mechanism, where there is a given link between police efficiency and crime for the treated area. The way the treatment affects police efficiency is through the increase of policemen, reducing response time and improving people's perception of safety, all of which translate into an improvement in police efficiency rather than into a change in the relationship between police efficiency and crime in the area. The unobservable potential outcome can then be expressed as follows:

$$E\left[Y\left(1, S_j\left(0\right)\right) \mid S_j\left(0\right) = s_{j0},\ X, t, W\right] = f_1\left(S_j\left(0\right),\ X, t, W\right) \tag{12}$$

We similarly define Eq. (11) for the control group:

$$E\left[Y\left(0, S_j\left(0\right)\right) \mid S_j\left(0\right) = s_{j0},\ X, t, W\right] = f_0\left(S_j\left(0\right), X, t, W\right) \tag{13}$$

Eq. (2) and the assumptions in Eq. (9) and Eq. (10) raise the possibility that both structural forms in equations (11) and (13) come from a more general equation, $f(\cdot)$, that uses the condition of the treatment as one of its inputs. In other words, the functional form of the treated group is equivalent to the control group when the dummy variable, D, is included (if treated, $D = 1$; if not treated, $D = 0$). Another option is that the functional forms are not quite comparable: on the basis of the spatial model presented by Eq. (2), it is likely some structural changes interact all the included regressors with the dummy variable D. This situation is not considered in this paper, because relying on the assumptions in Eq. (9) and Eq. (10) implies that there is at least one variable correlated with the potential outcomes and the treatment conditions that is not included in the matrix X.

$$f_1(S_j(1), X, t, W) = f(S_j(1), X, D = 1, t, W) \tag{14}$$

$$f_0(S_j(0), X, t, W) = f(S_j(0), X, D = 0, t, W) \tag{15}$$

Using Eq. (2), we can define the functional form as follows:

$$\begin{aligned} f(X, D, t, W) =& Y_{it} = \rho W_i Y_t + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t \\ &+ \alpha D_i * t_t + \alpha_2 W_i D + \delta W_i D * t_t + U_{it} \end{aligned} \tag{16}$$

Letting $g\left(S_j\right)$ represent how the mechanism is integrated into the functional form, we have

$$\begin{aligned} f(S_j, X, D, t, W) =& Y_{it} = \rho W_i Y_t + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t \\ &+ \alpha D_i * t_t + \alpha_2 W_i D + \delta W_i D * t_t + \gamma g_{it}\left(S_j\right) + U_{it} \end{aligned} \tag{17}$$

$g_{it}\left(S_j\right)$ can take several forms, such as $g_{it}\left(S_j\right) = S_{j,it}$, $g_{it}\left(S_j\right) = S_{j,it} + S_{j,it}X_{k,it}$ for a given variable k, or $g_{it}\left(S_j\right) = S_{j,it} + W_i S_{j,t}$. Thus, defining $g_{it}\left(S_j\right)$ as an external function allows us to simplify the estimation of $NATE$. Decomposing the definition of $NATE$, we have

$$\begin{aligned} NATE =& E[E\left[Y\left(1, S_j\left(0\right)\right) | X, t, W, S_j\left(0\right) = s_{j0},\ S_j\left(1\right) = s_{j1}\right] \\ &- E\left[Y\left(0, S_j\left(0\right)\right) | X, t, W, S_j\left(0\right) = s_{j0}, S_j\left(1\right) = s_{j1}\right]] \\ =& E[E\left[Y\left(1, S_j\left(0\right)\right) | X, t, W, S_j\left(0\right) = s_{j0}, \right] \\ &- E\left[Y\left(0, S_j\left(0\right)\right) | X, t, W, S_j\left(0\right) = s_{j0}\right]] \\ =& E[f_1\left(S_j\left(0\right), X, t, WD\right) \\ &- E\left[Y\left(0, S_j\left(0\right)\right) | X, t, W, S_j\left(0\right) = s_{j0}\right]] \end{aligned} \tag{18}$$

Keeping the values of $S_j(0)$ constant allows us to use Eq.(13) to express Eq. (18) as follows:

$$NATE = E[f_1\left(S_j\left(0\right),\ X, t, W\right) - f_0\left(S_j\left(0\right), X, t, W\right)] \tag{19}$$

Using Eq. (14) and Eq. (15), we have

$$NATE = E[f\left(S_j\left(0\right), X, D = 1, t, W\right) - f\left(S_j\left(0\right), X, D = 0, t, W\right)] \tag{20}$$

Given the functional form expressed in Eq.(17), the equation for the pretreatment period is as follows:

$$Y_{i0} = \rho W_i Y_0 + X_{i0}\beta + \alpha_0 D_i + \alpha_2 W_i D + \gamma g_{i0}\left(S_j\right) + U_{i0} \tag{21}$$

The following is the equation for the posttreatment period:

$$Y_{i1} = \rho W_i Y_1 + X_{i1}\beta + (\alpha_0 + \alpha)D_i + \alpha_1 + (\alpha_2 + \delta)W_i D + \gamma g_{i1}\left(S_j\right) + U_{it} \tag{22}$$

Since we are interested in the posttreatment specification, we have two options for modeling the transition between Eqs. (21 and 22): (1) we can assume that the structure of the mechanism variable has changed, implying that the parameter γ of Eq.(21) is different from the parameter γ of Eq.(22); or (2) we can assume that the structure of the mechanism variable has not changed, thereby making the parameter γ constant across specifications. Under both assumptions, the level of the variable is affected.

Recalling the argument presented above about the structural form condition for the unobserved potential outcome in Eq. (12), we rely on option (2) for our analysis, arguing that the structure of a mechanism is difficult to modify with an intervention, mostly because of the nature of the mechanisms considered in this analysis. We assume that the link between labor outcomes, police efficiency, and crime at the neighborhood level is stable in the short and medium run. Consider the case of the labor outcomes of informality and available income: there is a link between those outcomes and crime, which we have defined as $\gamma g_{it}(\cdot)$. After the treatment, families have access to a bigger pool of labor markets, which implies that the probability of finding a formal job is higher and the percentage of informal workers will likely decline. Also, families will spend less on transportation, so available income will be higher. These conditions account for improvements in the specified labor outcomes, but do not necessarily affect the relationship with crime at the neighborhood level. With this in mind, it seems that option (2) is a good fit for the exercise, and we can calculate the $NATE$. We first obtain the value of γ, which gives us

$$\begin{aligned} f(S_j, X, D, t, W) = Y_{it} =& \rho W_i Y_t + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t + \alpha D_i * t_t + \\ & \alpha_2 W_i D + \delta W_i D * t_t + \bar{\gamma} g_{it}\left(S_j\right) + U_{it} \end{aligned} \tag{23}$$

Given that the term $\bar{\gamma} g_{it}\left(S_j\right)$ is now a constant, we can rewrite the equation as follows:

$$\begin{aligned} \left(Y_{it} - \bar{\gamma} g_{it}\left(S_j\right)\right) =& \rho W_i Y_t + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t + \alpha D_i * t_t + \\ & \alpha_2 W_i D + \delta W_i D * t_t + U_{it} \end{aligned} \tag{24}$$

This equation can be also be written as:

$$\begin{aligned} \left(Y_{it} - \bar{\gamma} g_{it}\left(S_j\right)\right) =& \rho W_i \left(Y_t - \bar{\gamma} g_t\left(S_j\right)\right) + X_{it}\beta + \alpha_0 D_i + \alpha_1 t_t + \\ & \alpha D_i * t_t + \alpha_2 W_i D + \delta W_i D * t_t + \left(\rho W_i \bar{\gamma} g_t\left(S_j\right) + U_{it}\right) \end{aligned} \tag{25}$$

The $NATE$ will be similar to the ATE calculated in Eq.(6), but we must bear in mind that the mechanism effect has been subtracted from the dependent variable. Accordingly, the difference between this new estimation and that for ATE represents the impact of the treatment through this mechanism, as expressed by the following equation:

$$NATE = \alpha(I - \rho W)^{-1}\left(I + \delta\overline{WD}\right) \tag{26}$$

where α comes from the estimation of Eq. (25).

3 Data and Background

3.1 Dataset

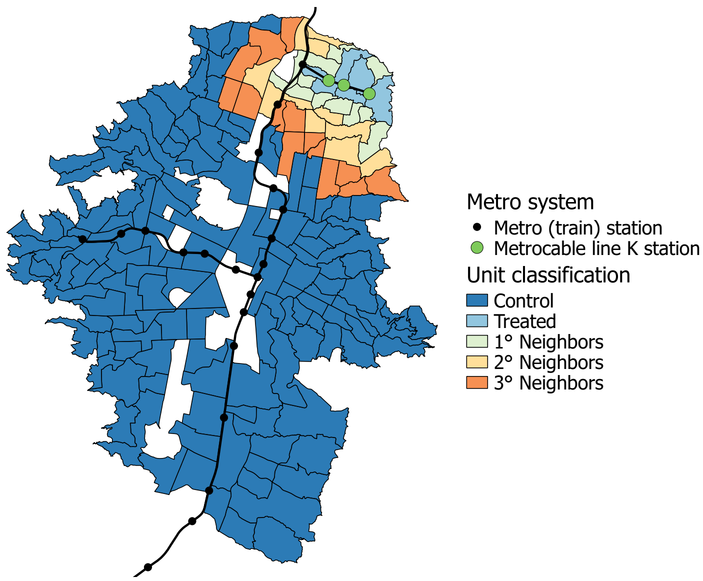
We collected georeferenced homicide data for the city of Medellin, Colombia, between 2003 and 2012 from the Information System for Safety and Coexistence (Sistema de Información para la Seguridad y Convivencia - SISC). We also use the Medellin household surveys of 2004, 2005, 2006, and 2012, which provide covariates and labor market outcomes. We set 2004 as the baseline for our study, and for posttreatment we used 2006 and 2012 to examine the short- and medium-run effects. The household survey pilot was administered in 2003, and the survey for 2004 was the first one widely available. That is why the baseline is set to 2004.

Unit of analysis: To guarantee the temporal stability of the spatial regions of analysis and the statistical robustness of the socioeconomic indicators calculated for each unit, we use the analytical regions delineated with the max-p-regions model devised by Duque et al. (2012a). The max-p-regions is a mixed-integer programming model that aggregates small neighborhoods into the maximum number of spatially contiguous analytical regions, such that each region is homogeneous in terms of socioeconomic characteristics and contains at least 30 surveyed households. The max-p-regions model has been used extensively in empirical socioeconomic analyses; examples of its usage in Medellin can be seen in Duque et al. (2017, 2015); López-Bazo et al. (2015); Patiño et al. (2014); Duque et al. (2013, 2012b, 2011).

Figure 1 presents the area of study, Medellin, divided into analytical regions. It also shows the Metro System, which is composed of two metro lines, the north-south line (A) and the west-center line (B), as well as the Metrocable (line K) in the northern part of the city. The analytical regions are classified as the control, treated, and first-, second- and third-order neighbors of treated regions. The definition of the first-, second-, and third-orders neighbors is given by shared-border criteria. First-order neighbors are those that share at least one border or vertex with the treated units, second-order neighbors are those that share at least one border or vertex with a first-order neighbor, and third-order neighbors are those that share at least one border or vertex with a second-order neighbor.

Mechanisms: In this paper, we propose two mechanisms to explain the association between the presence of the Metrocable and homicide rates: (1) increased accessibility to job opportunities, which reduces the spatial mismatch (Gobillon and Selod, 2007; Patacchini and Zenou, 2005; Andersson et al., 2014) and the rate of crime (Menezes et al., 2013; Scorzafave and Soares, 2009; Lochner, 1999); and (2) the presence of patrols and security cameras, as well as changes in urban attributes, which create defensible spaces that lead to crime reduction (Loukaitou-Sideris, 1999; Loukaitou-Sideris et al., 2001; Cozens, 2008; Patiño et al., 2014).

Figure 1: Mapping of treated neighbors, their first-, second- and third-order neighbors, and control units



Source: author's calculation.

Treatment and control regions: The treatment group is defined as the analytical regions through which the path of the Metrocable runs. Although the use of analytical regions is useful in terms of controlling for spurious spatial autocorrelation (Weeks et al., 2007), it is expected that some substantive spatial autocorrelation will cause some regions in the control group to be affected by the treatment. This expectation is related to the probability of being affected by the treatment (spillover effect) increasing as the degree of proximity to the treated regions increases.[5]

Earlier we introduced the idea of first-, second-, and third-order neighbors, our identifications of those analytical regions geographically close to the treatment regions. The main purpose of doing so is to quantify the treatment effect without arbitrarily imposing a specific boundary on the treatment effect. The Metrocable benefits those areas in the immediate vicinity, but it is not known a priori if those effects extend to those regions relatively close in terms of walking distance to the treatment regions. The first-order

[5]This argument is based on the first law of geography by Tobler (1970)

neighbors are on average 400 meters from a Metrocable station, second-order neighbors 770 meters, and third-order neighbors 1,330 meters. Not including the first-order neighbors means that we assume the impact is extremely localized and only affects areas closer than 400 meters, which is between a 5- and an 8-minute walk. Including high-order spatial lags will therefore reduce the need for such strong assumptions about the area affected by the treatment. Another reason is that using only the areas in which Metrocable stations are located yields a very small number of treatment units; that is why the first treatment group considered consists of those areas plus their first-order neighbors.

Outcome mechanisms: To measure the impact of increased patrolling and more defensible spaces, we use the number of captures not related to homicides (e.g., fraud, theft, and extortion).[6] For the mechanism related to increasing accessibility of job opportunities, we use the average income from labor activities and the percentage of formal workers (approximated using the percentage of workers enrolled in a social-security retirement program).

3.2 City background

In the period of analysis, Medellin had three mayors: Sergio Fajardo from 2004 to 2007, Alonso Salazar from 2008 to 2011, and Anibal Gaviria from 2012 to 2015. We will focus on some policies implemented in the first two mayoral terms, since the term of the last mayor overlapped with the last year of the period of analysis only. A brief summary of the relevant policies implemented will help provide the empirical context of this exercise, as well as the possible treats to the identification of the impact of the Metrocable.

As mentioned before, the Metrocable intervention entailed more than just a transportation system. The local government invested significantly in programs that complemented the Metrocable, with the administration of Sergio Fajardo largely overseeing this effort. Investment continued after the Metrocable began to operate in August of 2004: between 2004 and 2007 the city spent 6.6 times the construction cost of the Metrocable in 290 complementary programs. It modified 122,000 square meters of public space, increasing the amount per resident from 0.65 to 1.48 square meters. In addition, due to a tree-planting campaign the number of trees in the area rose from 154 to 527, improving both the appearance and air quality of the neighborhoods. Therefore, an evaluation of

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

the impact of the Metrocable must take into account more than just the investment in the transportation system; it must consider the entire investment in a neighborhood that occurs when a project of this magnitude is built.

Some funds of the Metrocable project did go to public libraries and recreational spaces. However, the rationale for this was in line with that for the investments made across the city as part of the Medellin city development plan, "Medellin la mas educada." Such plans focus on a specific policy issue, which in the case of "Medellin la mas educada" was education. It covered investment in infrastructure, assistance to schools, and provision of meals for students. By December 2007, around 45 new schools and libraries had been built, 237 had improved their infrastructure, and more than 600 had gone through a maintenance program. The city saw significant progress in education: the coverage of daycare and schooling for children up to 5 years old went from 18.8 percent in 2004 to 32 percent in 2007, and the coverage for students in secondary education went from 71 percent in 2004 to 80.5 percent in 2007. These efforts were targeted at public schools, which are present in most parts of the city.

During 2008–2011 one of the most remarkable policy initiatives was "Medellin Solidaria," the focus of which was improving the quality of life of families in extreme poverty and vulnerable conditions. The program was directed at predominantly low-income families. Between 17 and 20 percent of the total coordinators of the program were assigned to the Metrocable area of influence. As a result of the program, almost 87 percent of households with children experienced an increase in the level of school attendance.

Some policies extremely localized in nature were implemented with a focus on economic development, with the transformation of the city's downtown being a notable example. This area received around USD 150 million between 2004 and 2008 to enhance economic activity and to attract consumers who stopped visiting the area due to safety concerns. Another relevant program promoting entrepreneurship saw the city invest more than USD 50 million. The focus of this program was to incentivize entrepreneurs and create a favorable environment for start-ups and small and medium companies. This program has a flagship building located in the neighborhood of the state public university, close to downtown. Most of the assistance to entrepreneurs, largely financial support, is facilitated by staff in that building, but some satellite buildings exist around the city.

The year 2006 saw the initiation of a project providing sex-ed advice intended to prevent teen pregnancy to residents of the Metrocable area of influence and neighborhoods close to it, which was subsequently expanded to other parts of the city. More than 12,000 individuals received counseling between 2006 and 2008 and almost 10,000 received contraceptive methods. It is difficult to know whether this had an impact relevant to the effects we estimated, especially for the mechanism related to labor outcomes. However, given the population targeted and the improvements in education coverage and dropout rates, this kind of program does significantly affect school registration and attendance.

4 Results

4.1 Summary Statistics

Table 7 in the appendix presents some summary statistics at the city level by Treated+1st neighbors and the control group.[7] The trend in homicides for the analytical units shows a larger decrease between 2004 and 2006 than between 2004 and 2012. However, at the city level, there is a small increase in the homicide rate for 2012. Labor income shows a relatively stable trend with a slight, insignificant decrease between 2004 and 2006. The percentage of informality, defined as the percentage of workers not enrolled in a social-security retirement system, shows that almost half of the working population is in the informal sector. The share of the married population has changed slightly over time, but has remained relatively constant at around 25 percent. Approximately 30 percent of youth (15 to 19 years old) do not attend school, and the percentage of the population who has pursued secondary studies (complete or incomplete) is approximately 40 percent.

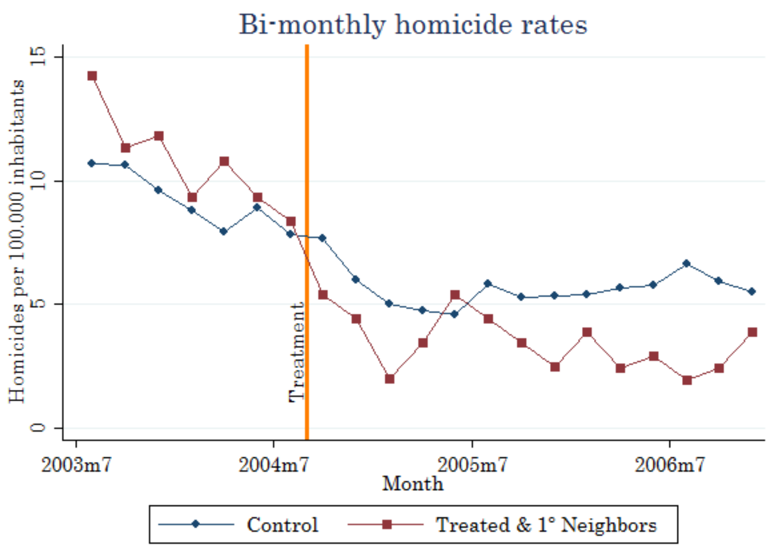
However, these results hide some heterogeneity across treated and untreated units. In an exhaustive analysis of means and summary statistics broken down by treatment and control groups, we found that in our baseline, the median of homicides is higher in the treated spatial units than that in untreated spatial units. Following the implementation of the Metrocable, treated units presented slightly fewer homicides compared to untreated ones. As for labor income, untreated units demonstrate higher levels than treated ones over the entire period of analysis. Some of our socioeconomic covariates show differences between untreated and treated groups in terms of cultural and economic characteristics. The married population is higher in the treated areas, as is the percentage of those who have some but not complete secondary education. The average number of children per

[7]Complete summary tables upon request.

family is also higher in treated regions.

Figure 2 shows the homicide rate per 100,000 inhabitants for two groups of neighborhoods: (1) treated neighborhoods and their first-order neighbors and (2) control neighborhoods. Before the treatment, both groups presented a negative trend, and the treated units were more violent than the control group. After the treatment, the control group showed a higher homicide rate for almost all periods.

Figure 2: Pre & post-treatment homicide behavior



Source: author's calculation.

Following the general trend in the research about impact evaluation, we rely on the common trend assumption, which is embedded in Eq. (9) and Eq. (10). Figure 2 tries to get a sense of how plausible this assumption is, given that both groups—control and treatment— seem to show similar trends. The treatment group, comprising the direct treatment regions and their first-order neighbors, behaves noisier than the control group; however, this is a result of the fewer number of units in the treatment (17 analytical regions) and the time frequency (2 months). If one ignores the noise typical of the treatment group, the trend before the treatment is similar between the groups and after the treatment the difference in the rate of homicides between the two groups starts to increase in favor of the treated units. We repeat the exercise using a time frequency of three months and including the second-order neighbors in the treatment group. As we expected, the lines are smoother and the main idea still holds.

4.2 Main Results

Table 1 presents the results of the estimations using treated units, treated units plus first-order neighbors, treated units plus second-order neighbors, and treated units plus third-order neighbors. We also differentiate between regular and SDiD estimations.

The estimates for the short-term impact (2004–2006) using the regular difference-in-differences approach indicate a negative effect of the cable car line in terms of homicide reduction, but some of these results are statistically insignificant. The point estimates suggest the implementation of the cable car did have an effect on the treated units alone, although we should note the small sample size, which drives the relative high standard errors compared to the other estimations. This impact does become larger and statistically significant when we consider the treated and first-order neighbor units, but the effect vanishes when the second- and third-order neighbors are included.

As for the medium-term effects (2004–2012), results from the ordinary least square (OLS) estimates are highly encouraging: While we found statistically insignificant effects for the treated units, when the first-, second-, and third-degree neighbors are included, the impact of the Metrocable is statistically significant at a 1 percent level of confidence and is much larger than that identified for the short term. In fact, we could infer that for first-order neighbors, the homicide rate decreased by $100[exp(0.72) - 1] = 51$ percent. These figures should be considered carefully in order to avoid misinterpretation. This 51 percent indicates that the homicide rate for the treated units decreased by 51 percent more than that for the control group—in other words, if the rate for the control group decreased by 20 percent, the rate for the treated units should have decreased by 30.3 percent. This effect declines with the inclusion of second-order neighbors, reaching a total impact of 44 percent. Finally, when including third-order neighbors, the impact becomes 46 percent. A spatial difference-in-differences approach yields similar results.

Another important finding in Table 1 is that the standard errors decrease sharply as we move from treated units to third-order neighbors, which strongly suggests an increase in the statistical power. This decrease also indicates the high possibility that the coefficient of the treatment is indeed negative, but due to the small sample size, we failed to obtain statistical significance.

In summary, we have found strong and sizable time and distance effects in homicide reduction around the Metrocable areas. Our SDiD model, which includes controls as covariates, shows a reduction in the homicide rate of approximately 51 percent in the neighborhoods treated by the Metrocable and their first-level neighbors. When we increase the area of influence to include second-order neighbors, the impact decreases by 7 percentage points. Finally, when we include third-order neighbors, the impact increases by 1.5 percentage points. These results provide evidence of a spatial decay function of the Metrocable and an increase in impact over time.[8]

4.3 Mechanisms

As presented in the previous subsection, the implementation of the Metrocable reduced homicides in the affected areas (first-, second-, and third-order neighbors) by approximately 51, 44, and 46 percent, respectively. We decompose this impact into its constituent mechanism effects (i.e., we clarify the causal pathways through which this reduction in homicides was achieved). To this end, we consider two mechanisms related to deterrence and the labor market. As mentioned in earlier sections of this paper, many other mechanisms might have contributed to the decrease in the crime rate related to the Metrocable intervention. However, we focus only on the following two, which represent major topics in crime analysis: labor accessibility and police efficiency.

Table 2 shows the full impact estimated for the short and medium terms, and each of the impacts is broken down by the $NATE$, the average treatment effect net of the mechanism. For each time period of analysis, we calculate the impact net of the socioeconomic mechanism, net of the police mechanism, and net of both mechanisms together. Using the total impact and the impact net of a mechanism, we can calculate the percentage of the total impact that the mechanism accounts for (which is presented in the third row for each mechanism, whenever the mechanism is significant at standard levels). If both mechanisms are relevant to the explanation of why the Metrocable led to crime reduction in that area, the percentage of the total impact for which both mechanisms (taken

[8]Additional analysis of two other types of crimes, auto theft and theft from commercial establishments, is provided in the appendix D. It suggests that in the short run the Metrocable increases the number of auto thefts, due to greater accessibility of cars in the area, but that in the medium run there is a negative effect—which is, however, lower than that observed for homicides.

Table 1: Results for Traditional and Spatial Difference-in-Differences

Dependent: ln(Homicides+1)	**Treated**		**Treated + 1st Neighbors**		**Treated + 2nd Neighbors**		**Treated + 3rd Neighbors**	
Difference-in-Differences								
			Short Impact (2004-2006)					
Total Impact	-0.390	*	-0.511	***	-0.167		-0.092	
	(0.23)		(0.20)		(0.19)		(0.17)	
	-32.28%		-40.04%		-15.36%		-8.82%	
			Medium Impact (2004-2012)					
Total Impact	-0.630	*	-0.721	***	-0.587	***	-0.611	***
	(0.37)		(0.22)		(0.20)		(0.17)	
	-46.75%		-51.40%		-44.39%		-45.72%	
Spatial Difference-in-Differences								
			Short Impact (2004-2006)					
Total Impact	-0.388	*	-0.511	***	-0.163		-0.089	
	(0.23)		(0.19)		(0.18)		(0.17)	
	-32.17%		-40.00%		-15.00%		-8.54%	
			Medium Impact (2004-2012)					
Total Impact	-0.633	*	-0.721	***	-0.585	***	-0.612	***
	(0.37)		(0.22)		(0.20)		(0.17)	
	-46.89%		-51.40%		-44.29%		-45.78%	
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. The spatial unit of analysis is the analytical region.

together) account should be at least as much as the sum of the individual impacts.

Socioeconomic mechanism: One of the mechanisms through which the Metrocable may be reducing homicides is the economic inclusion of people in the city. People can access jobs and increase their productivity due to the reduction in transportation costs, which include temporal costs, as well as the increase in access to new job opportunities (Gobillon and Selod, 2007; Patacchini and Zenou, 2005; Andersson et al., 2014). To further explore this mechanism, we examine the labor income and the percentage of formal employees. As can be inferred from Table 2, for the treated units and their first-order neighbors in the short term, approximately 13 percent of the total effect can be attributed to the socioeconomic mechanism, an effect that tends to decrease in the medium term to 5 percent.

In the medium run, when we consider a broader area of impact, the socioeconomic mechanism accounts for 3 percent of the total impact for treated plus second-order neighbors and 2 percent for third-order neighbors. The impact of the socioeconomic mechanism decreases with distance, which is not surprising. This mechanism is the more locally concentrated of the two analyzed in this paper. Neighborhoods far away from the Metrocable may not experience the significant reduction in travel costs and the same accessibility advantages created by the new system. This finding concurs with the research mentioned above that has found accessibility to the labor market plays an important role in reducing crime crime rates.

Deterrent mechanism: The second potential mechanism for the reduction in homicides is related to deterrence. The implementation of the Metrocable also acts as a deterrence mechanism due to the increased number of policemen in the area, which, in turn, may result in a larger number of arrests. We found that nearly 17 percent of the effect for treated units plus first-order neighbors can be explained by this mechanism in the short run; however, this effect decreases to 13 percent in the medium term. The impact is particularly significant for second- and third-order neighbors. For the medium term, in which all the coefficients remain statistically significant, the deterrence mechanism accounted for 17 percent of the total reduction in the homicide rate in the treated units plus their second-order neighbors and 21 percent in the treated units plus their third-order neighbors.

The new facilities are not only equipped with surveillance cameras, but also house a permanent police presence. These policemen monitor the stations and adjacent zones. All stations are widely accessible to the public, and visibility is a prior characteristic. Although the police are not allowed to make rounds around the neighborhood, their presence acts as a deterrent for incipient criminals, mainly those especially concerned with being caught. The prevalence of the impact seems to be clear evidence that no crime displacement takes place; however, this finding merits further analysis.

As mentioned earlier, the impact of both mechanisms (socioeconomic and deterrence) together should not be lower than the sum of the individual impacts, if the estimations are relevant and accurate. Both mechanisms for the treated units plus first-order neighbors in the short run account for 42 percent of the intervention's total impact. Although this figure decreases in the medium term, the impact does spread to adjacent zones, as both mechanisms account for 22, 25, and 28 percent of the intervention's total reduction for the treated plus first-order, second-order, and third-order neighbors, respectively. The impact of both mechanisms together being greater that the individual sum is an example of a multisectoral policy implementation, which, in this scenario, was unintended; the mechanisms identified in this paper worked together to reduce crime in the treated areas. In addition, we can conclude from these results that some aspects of the impact will vanish over time, but in a spatial framework the impact should have an effect on units linked somehow to the treated units.

4.4 Robustness Checks

Units of analysis (neighborhoods): One of the main concerns in this study is the units of analysis proposed. We are working with analytical regions designed with the max-p-regions model. Although the minimization of aggregation bias makes these regions particularly safe in statistical terms, the usage of these regions may not enable the direct implementation of public policy, because they do not coincide with the administrative units.

To address this matter, we propose a robustness check, in which we use the neighborhoods of the city instead of the analytical regions. The aim of this exercise is to ensure that our main results are not driven by the composition of the spatial units of analysis. Table 3 shows both the traditional and the spatial difference-in-differences results for this exercise. The variation between the impact estimated using the analytical regions and that using the administrative neighborhoods is consistently small.

The SDiD shows reductions in the homicide rate of 49, 45, and 42 percent in the medium term for treated neighborhoods plus first-, second-, and third-order neighbors, respectively. The figures for the analytical regions are similar: 51, 44, and 46 percent for treated units plus first-, second-, and third-order neighbors, respectively.

Although we presented some reasons above to support the use of analytical regions, a reiteration of them here in a summary, after ensuring that there is no considerable difference between them, is in order. The first reason is statistical: We should conduct the analysis based on variables representative at the selected spatial unit of analysis.

Table 2: Mechanism decomposition within the Spatial Difference-in-Differences

Dependent: ln(Homicides+1)	**Treated**		**Treated + 1st Neighbors**		**Treated + 2nd Neighbors**		**Treated + 3rd Neighbors**	
			Short impact (2004-2006)					
Total Impact	-0.388	*	-0.511	***	-0.163		-0.089	
	(0.23)		(0.19)		(0.18)		(0.17)	
	-32.17%		-40.00%		-15.00%		-8.54%	
Net of Economic mechanism	-0.350		-0.443	**	-0.117		-0.051	
	(0.22)		(0.19)		(0.18)		(0.16)	
	-		13.37%		-		-	
Net of Police mechanism	-0.359		-0.422	**	-0.138		-0.062	
	(0.22)		(0.19)		(0.17)		(0.15)	
	-		17.45%		-		-	
Net of Both mechanisms	-0.278		-0.298		-0.049		0.016	
	(0.22)		(0.19)		(0.17)		(0.15)	
	-		41.76%		-		-	
			Medium impact (2004-2012)					
Total Impact	-0.633	*	-0.721	***	-0.585	***	-0.612	***
	(0.37)		(0.22)		(0.20)		(0.17)	
	-46.89%		-51.40%		-44.29%		-45.78%	
Net of Economic mechanism	-0.577		-0.687	***	-0.568	***	-0.600	***
	(0.37)		(0.22)		(0.20)		(0.17)	
	-		4.83%		2.92%		2.02%	
Net of Police mechanism	-0.480		-0.629	***	-0.486	***	-0.483	***
	(0.37)		(0.21)		(0.18)		(0.16)	
	-		12.80%		16.87%		21.06%	
Net of Both mechanisms	-0.376		-0.560	***	-0.440	**	-0.443	***
	(0.37)		(0.21)		(0.18)		(0.16)	
	-		22.35%		24.71%		27.61%	

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages displayed for total impact correspond to the impact on homicides calculated using the formula to approximate the marginal impact of a dummy in a log functional form. The percentages shown for both mechanisms correspond to the proportion of the total impact for which each mechanism accounts (obtained as the difference between the coefficients for total impact and for the value net effect of the mechanism over the total impact coefficient). Only the percentages for significant regressions are displayed. Analysis conducted using analytical regions.

The exercise using the neighborhoods is more biased, due to its strong relationship with the survey design. The second is practical: Because of the definition of our theoretical framework, all the matrices are designed to work with a balanced dataset, and if at any time observations of one neighborhood are missing for one year, the unbalanced dataset will not enable any estimation. Ultimately, after this robustness check, and given that there is not a big difference across the two options, we conclude that there are no constraints on our use of analytical regions.

Table 3: Traditional and Spatial DiD using Neighborhoods

Dependent: ln(Homicides+1)	**Treated**		**Treated + 1st Neighbors**		**Treated + 2nd Neighbors**		**Treated + 3rd Neighbors**	
Difference-in-Differences								
			Short Impact (2004-2006)					
Total Impact	-0.430	*	-0.501	**	-0.133		-0.041	
	(0.23)		(0.20)		(0.17)		(0.16)	
	-34.98%		-39.38%		-12.47%		-4.00%	
			Medium Impact (2004-2012)					
Total Impact	-0.619	*	-0.676	***	-0.605	***	-0.561	***
	(0.32)		(0.22)		(0.18)		(0.17)	
	-46.17%		-49.12%		-45.39%		-42.96%	
Spatial Difference-in-Differences								
			Short Impact (2004-2006)					
Total Impact	-0.435	**	-0.523	***	-0.150		-0.058	
	(0.22)		(0.20)		(0.16)		(0.16)	
	-35.27%		-40.74%		-13.89%		-5.64%	
			Medium Impact (2004-2012)					
Total Impact	-0.588	*	-0.676	***	-0.601	***	-0.553	***
	(0.31)		(0.22)		(0.18)		(0.17)	
	-44.45%		-49.12%		-45.18%		-42.49%	
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.

Crime displacement: A common question when implementing strategies for crime reduction is whether the intervention actually reduces crime or just displaces the phenomenon to another location. To test whether the Metrocable generated a displacement effect, we ran our main estimation sequentially (i.e., instead of estimating a unique coefficient for the influence area, we estimated one coefficient for treatment and one coefficient each for first-, second-, and third-order neighbors). Although this approach allows us to identify changes in the impact for each area, it does increase the number of coefficients required for the estimation, which costs us some efficiency.

Table 4 shows the results of the robustness check. The aim of this exercise is to check whether the estimated coefficient is weakened when more-distant neighborhoods are considered in the analysis; by "weakening," we mean a reduction in magnitude or an increase in standard errors. The results show that the inclusion of additional neighborhoods that are progressively farther away from a Metrocable station does not lead to significant changes in coefficients, nor does it change their standard errors. Thus, there is no evidence of the existence of a crime displacement effect.

Another concern related to crime displacement is the possible change in criminals' places of residence. Crime displacement refers not only to crime happening in another place, but also to criminals moving to other neighborhoods. In the studied case, some criminals, due to the increased presence of police, may decide to move to other neighborhoods. We do not have access to criminal migration patterns, so we must look at patterns for all residents. Using the data from the "Quality of Life" survey, we found that in 2006, the level of migration in the treated neighborhoods was 7.49 percent, and in untreated neighborhoods, it was 10 percent. In 2012, these figures were 9 and 11 percent, respectively. These results indicate that migration may not be a major issue for our analysis.

Genetic Matching: This robustness check aims to ensure that the results are not driven by the number of control units included. Our results consider the control group to be the spatial units that are not in the treatment group and are within the urban area of Medellin. This classification may raise some doubts on the basis that this is a convenient assumption.[9]

To address this potential downside, we implement a genetic matching algorithm to find a more similar control group. Then, we estimate the difference-in-differences for the short and medium term and for first-, second-, and third-order neighbors. With this approach, we do not apply spatial difference-in-differences, because we no longer have a geographic

[9] In contrast to this approach, other studies use a considerably lower ratio of treated to control units: Di Tella and Schargrodsky (2004) has 14 treated and 53 control; Corsaro et al. (2012) has 122 treated and 1,583 control. Similarly, Benavente et al. (2011) used 12 treated and 84 control.

Table 4: Sequential estimations.

Dependent: ln(Homicides+1)								
	Short impact (2004-2006)							
	Treated		1st Neighbors		2nd Neighbors		3rd Neighbors	
Treated	-0.388	*						
	(0.23)							
Treated + 1st Neighbors	-0.415	*	-0.564	**				
	(0.23)		(0.26)					
Treated + 2nd Neighbors	-0.388	*	-0.527	**	0.389			
	(0.22)		(0.26)		(0.31)			
Treated + 3rd Neighbors	-0.392	*	-0.528	**	0.392		0.055	
	(0.23)		(0.26)		(0.32)		(0.26)	
	Medium impact (2004-2012)							
	Treated		1st Neighbors		2nd Neighbors		3rd Neighbors	
Treated	-0.633	*						
	(0.37)							
Treated + 1st Neighbors	-0.684	*	-0.742	***				
	(0.36)		(0.26)					
Treated + 2nd Neighbors	-0.717	**	-0.769	***	-0.319			
	(0.36)		(0.26)		(0.33)			
Treated + 3rd Neighbors	-0.785	**	-0.829	***	-0.378		-0.534	**
	(0.37)		(0.26)		(0.34)		(0.27)	

Source: author's calculation
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. For each row named as Treated, Treated plus first-, second-, and third-order neighbors the impact of each group is estimated separately. For example, the last row of Treated + 3rd Neighbors has four coefficients: the first is associated with the treated units only, the second with first-order neighbors only, the third with second-order neighbors only, and the fourth with third-order neighbors only. The spatial unit of analysis used is the analytical region.

continuum on the basis of which to calculate the spatial neighboring relationships (W matrix). Table 5 shows the results of this exercise. The upper panel of the table contains the results using the analytical regions, and the bottom panel presents the results using the administrative neighborhoods. The results are consistent across specifications and reinforce the finding that the Metrocable had a significant impact on the treated units. In fact, the results of this robustness check are greater in magnitude, with most percentages above 50 percent. This result is not surprising, since the analysis of a given control group can overestimate the impact by not taking into account the decreasing trend in the city's homicide rate.

Table 5: Genetic Matching & Difference-in-Differences

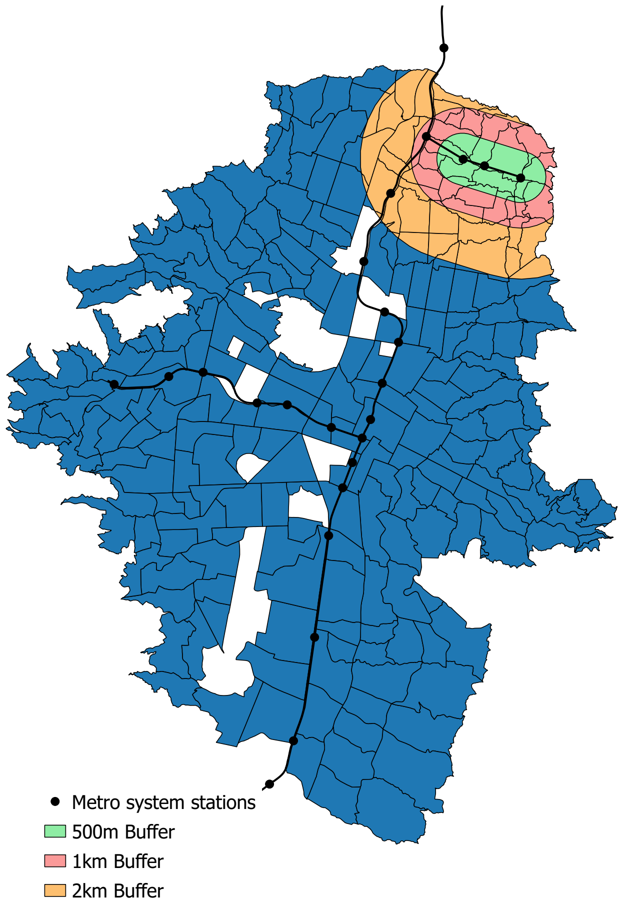
Analytical regions as spatial units						
	1st Neighbors		**2nd Neighbors**		**3rd Neighbors**	
Short impact (2004-2006)	-0.531		-0.532	**	-0.410	*
	(0.32)		(0.24)		(0.21)	
	-41.21%		-41.28%		-33.61%	
Medium impact (2004-2012)	-1.008	***	-0.817	***	-0.840	***
	(0.30)		(0.24)		(0.20)	
	-63.50%		-55.82%		-56.83%	
Neighborhoods as spatial units						
	1st Neighbors		**2nd Neighbors**		**3rd Neighbors**	
Short impact (2004-2006)	-0.248		-0.284		-0.175	
	(0.26)		(0.23)		(0.23)	
	-22.00%		-24.72%		-16.07%	
Medium impact (2004-2012)	-0.554	*	-0.830	***	-0.688	***
	(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 for the slope and elevation of the units of analysis. As we expected, those variables are statistically significant in terms of explaining the probability of being treated. The results of this process are available upon request.

Buffers: Our last robustness check consists of using a symmetric definition for the area of influence (i.e., buffers) instead of a neighborhood ordering based on administrative units. In this case, we take advantage of homicide data at the point level to identify events that occur within 500 meters, 1 kilometer, and 2 kilometers of the Metrocable stations. The resulting buffers are presented in Figure 3.

This approach works under the premise that the administrative borders are somehow invisible to people, whereas based on the first law of geography (Tobler, 1970), the effect of the Metrocable should decay with distance. Table 6 shows the results of using buffers to identify treated and control units. The results for the impact in the buffers around the Metrocable line with a radius of 500 meters are similar to those for treated units, because the treated neighbors are, on average, 500 meters from a Metrocable station. The impact

Figure 3: Buffers for the spatial relationship



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

is much greater on the units 1 kilometer away than on those units 2 kilometers away. In the 1-kilometer radius, the implementation of the Metrocable decreased homicides in the medium run by 47 percent more than in the control group, but this figure falls to 44 for the buffer of 2 kilometers. The estimated impacts are similar to the main results previously discussed, and they strongly support the strategy chosen.

Table 6: Buffer Treatment Assignment with Difference-in-Differences

Dependent: ln(Homicides+1)	500m		1km		2km	
Short Impact (2004-2006)						
Total Impact	-0.335		-0.313		-0.047	
	(0.21)		(0.20)		(0.18)	
	-28.45%		-26.88%		-4.63%	
Net of Economic mechanism	-0.304		-0.255		-0.035	
	(0.21)		(0.20)		(0.17)	
	-		-		-	
Net of Police mechanism	-0.399	*	-0.265		-0.055	
	(0.22)		(0.19)		(0.16)	
	-		-		-	
Net of Both mechanisms	-0.300		-0.153		0.015	
	(0.23)		(0.19)		(0.16)	
	-		-		-	
Medium Impact (2004-2012)						
Total Impact	-0.334		-0.628	***	-0.578	***
	(0.26)		(0.22)		(0.19)	
	-28.42%		-46.63%		-43.91%	
Net of Economic mechanism	-0.324		-0.582	***	-0.572	***
	(0.27)		(0.22)		(0.19)	
	-		7.38%		1.16%	
Net of Police mechanism	-0.347		-0.521	**	-0.477	***
	(0.25)		(0.21)		(0.17)	
	-		16.97%		17.52%	
Net of Both mechanisms	-0.296		-0.449	**	-0.431	**
	(0.26)		(0.21)		(0.17)	
	-		28.43%		25.48%	

Source: author's calculation

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Percentages displayed for total impact correspond to the impact on homicides calculated using the formula to approximate the marginal impact of a dummy in a log functional form. The percentages displayed under both mechanisms correspond to the proportion of the total impact that each mechanism accounts for (obtained as the difference between the coefficients for total impact and for the value net effects of the mechanism over the total impact coefficient). Only the percentages for significant regressions are displayed. Analysis conducted using analytical regions.

5 Discussion

Innovations in public infrastructure can do a great deal to promote economic and human development and improve quality of life, especially in cities, where space is both limited and geographically dissimilar. As an example of their positive impacts, these types of interventions may contribute to reductions in crime payoffs in urban settings through various channels, such as deterrence and social inclusion (Glaeser and Sacerdote, 1999; La Vigne, 1996; Crowe, 2000; Cozens, 2008). Over the past few years, cable cars have emerged as a viable mode of public transportation for densely populated cities located within challenging terrain. However, there exists little empirical evidence on the effects of this form of innovative public infrastructure on outcomes such as criminality in surrounding neighborhoods. Given the growing use of such systems in the developing world, it is of paramount importance to understand how the establishment of cable cars impacts crime, especially in areas with high criminality.

This paper is driven by a research question that focuses on the relationship between investments in urban public transportation and their impact on crime (in terms of homicide rates). Using a rich spatial dataset and myriad econometric techniques, we estimate the short- and medium-term effects of the implementation of cable cars (Metrocable) in Medellin, Colombia.

The Metrocable, which opened in 2004, has attempted to integrate isolated areas of the city into the public transportation system. Metrocable stations can serve as a source of security, as the probability of criminals being apprehended increases with their appearance, and the perception of deterrence is greater in areas in which new stations are located.

We found strong evidence that the implementation of the Metrocable reduced crime in the areas neighboring those in which this infrastructure was located, but the results were not statistically significant. However, we did find evidence supporting spatial spillover of the Metrocable: our estimation results using a spatial difference-in-differences approach suggest that the Metrocable had a large and significant impact on reducing homicides. Those neighborhoods in which the Metrocable is located (and their first-order neighbors) experienced a decrease in the level of homicides by an average of 51 percent more than the overall decrease in the homicide rate experienced by all neighborhoods of the city over the same period.

These effects tended to be stronger in the medium run than in the short run. We explored two different mechanisms through which these effects may operate: the inclusion effect and the deterrence effect. Both mechanisms explain more than one-third of the effect in the short run and more than one-fourth of the effect in the long run, with the deterrence mechanism being stronger than the inclusion mechanism.

The implications of our results are fourfold. First, our results contribute to the limited literature on the effects of innovation in infrastructure and their unintended outcomes such as crime reduction. More specifically, our findings reinforce the empirical literature that supports the use of public infrastructure as a tool to improve the quality of life within cities. Second, our results highlight the importance of considering spatial effects when estimating the impacts of these interventions, given the spatial correlation that exists between neighborhoods within a city. Third, a significant portion of the effects of the implementation of the Metrocable on crime is indirect, which is natural, since this type of infrastructure was not intended to reduce crime. The reduction of crime is achieved through a series of channels such as deterrence and inclusion, and thus policies that boost these channels may result in greater positive effects with regard to crime.

Finally, our results highlight the efficacy of innovative forms of public transportation in cities with limited space, difficult terrain, and high levels of crime. While we do not claim the external validity of our results, these results are, for the most part, strong and significant, highlighting the potential benefits of innovative public infrastructure interventions within cities.

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Appendix A Endogeneity of captures

To measure the police mechanism – by which a higher police presence increases the probability of apprehension and thereby deters crime – we used captures as a proxy. However, in this context, in which we have more than one period of time, we faced the problem of possible endogeneity across the variables of captures and homicides. More captures deter crime, but there are no captures if there are no homicides. To address this problem, we took advantage of the extremely disaggregated information we have for captures. We identified the type of captures, determining whether they were for homicides, drug-related crimes, extortion, sex-violence, or one of many other classifications. We used a simple strategy to test how concerned we should be about this problem by applying a similar strategy to the Granger causality and dynamic panels. The following equation summarizes the strategy used:

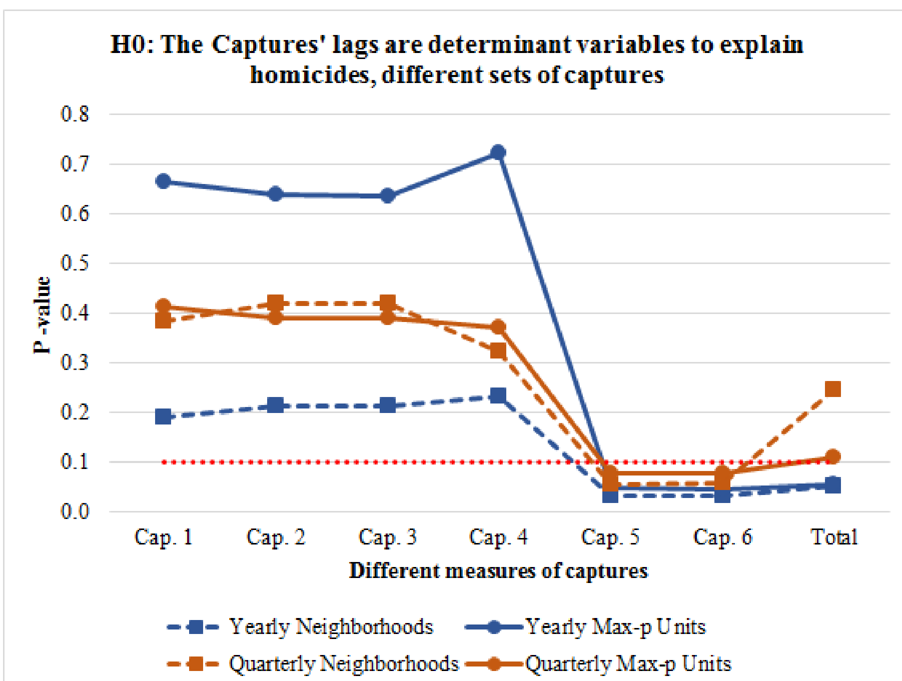
$$Hom_{i,t} = \alpha_0 + \sum_{j=1}^{p} \rho_j Hom_{i,t-j} + \sum_{m=0}^{q} \beta_m Cap_{i,t-m}^{(k)} + u_{i,t} \tag{27}$$

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

The logic here is fairly simple. We included the homicide lag because we are dealing with a dynamic panel, and thus, the history of homicides should matter. Then, if endogeneity between captures and homicides exists, using the captures' lags as instrumental variables will ensure that the captures' lags are statistically significant in explaining homicides (i.e., the joint t-test on the β_m will be different from zero, and the p-value will be below the common confidence level, 10%). To test this, we use different definitions of captures ($Cap^{(k)}$, where $K = 1, 2, ..., 6$), which are defined in Table 8.

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

Figure 4: Endogeneity test for different capture measurements



Source: author's calculation
Note: the orange lines represent the quarterly models, while the blue lines are the yearly models. The red dotted line on 0,1 p-value represents the standardized threshold for rejection of the null hypothesis. The main models used $Cap^{(2)}$, but as it shows, $Cap^{(1)}$ through $Cap^{(4)}$ work.

Appendix B Monthly structure

Our database allows us to run some models on a monthly structure. Although we cannot have any particular covariates for this exercise, we include month-year fixed effects to account for all specific events during that period. We also use a similar estimation strategy as the main estimation. We divide the impact of the direct effect (the effect of the treatment on the treated) and the indirect or spatial component (the effect on those untreated but located close to the 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 does not strongly identify structural relationships.

Table 9 presents the results of a model in which the log of the homicides in the neighborhood i is the dependent variable and is a function of the homicides in its neighbors (rho) if it and its neighbors have been treated. The inclusion of the neighbors follows the structure stated by Anselin and Smirnov (1996), who argued that using the contiguity matrix enables the building of a matrix that contains greater spatial lags, resulting in matrices that can identify the second-order neighbors (neighbors of neighbors) until umpteenth-order neighbors. The first panel of the table "Effect Treatment ($t_0 - 2006m12$)" contains the results of this calculation. In this case, the impact is negative for both direct and indirect effects, but the indirect effect is statistically significant. This result emulates exactly what we have seen before. Due to the reduced 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 the first-, second-, and third-order neighbors, shows a significant decrease in homicides. This analysis was conducted for the period from 2003 to 2006, and the treatment variable equals 1 for all periods after the intervention in July 2004.

The following three panels also contain the direct, indirect, and total impacts of the treatment, but we break down the treatment variable by period, which allows us to identify the exact period when the intervention had a significant impact. The relevant periods for us are the first 6 months after the treatment ($t_0 - t_5$), between 6 and 12 months of the treatment ($t_6 - t_{11}$) and between 12 and 18 months ($t_{12} - t_{17}$). Additionally, we want to corroborate if there is any particular effect driving the results prior the intervention, so we added a variable that equals one for the 6 months prior the Metrocable construction

(t_{-6}). In all cases, this last variable was insignificant, which serves as evidence that there were no pre-trend effects driving the results of this study.

Regarding the direct impact, the treatment shows some effect after six months of the intervention, meaning that neighborhoods where the Metrocable is located began to experience greater reductions in homicides than the rest of the city between six months and one year after the construction. However, most of the indirect impact began six months later. The neighborhoods near the Metrocable experienced greater reductions in the homicide rate after more than one year of the construction. These figures sustain our hypothesis and the results discussed in the paper: the impact of the intervention spreads across the neighborhoods if there is indeed a spatial link between them. The intervention begins to show an impact in 2006.

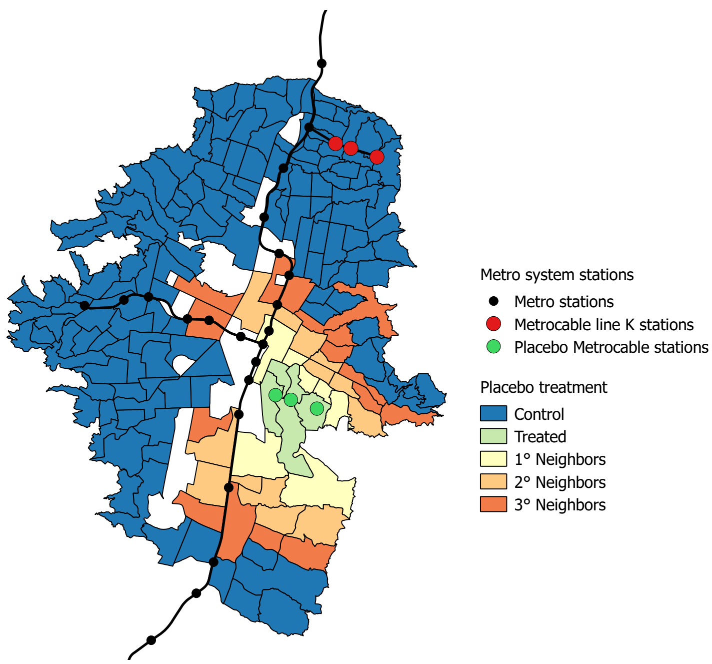
Appendix C Placebo test

To identify the impact that the new public transportation intervention had on crime, this study concludes with what is commonly called the "placebo test." In this paper, we have shown satisfactory results relating to the intervention of the Metrocable and its significant impact on decreasing homicides in the treated areas and their surrounding zones. We would also like to show that the results obtained are not driven by a general reduction pattern in the homicide rate of the city nor confounded significantly with other public interventions. To do so, we defined a "placebo" Metrocable, or a fake Metrocable.

In Figure 5, light green dots show the stations of our fake Metrocable. We tried as much as possible to ensure that the Metrocable fit in an area with similar characteristics, specifically in slope and elevation, to the one where it was actually built. Additionally, the length of the fake Metrocable is the same as that of the real one, and the distance between the stations remains unchanged. Similar to our estimate of the impact of the real Metrocable, we defined the units treated as those in which any Metrocable facility was located. Then, we identified their first-, second-, and third-order neighbors.

Finally, we ran the main model using this fake Metrocable as the intervention. In terms of expectations, if the Metrocable is a real deterrent of crime, we should not see any impact in this exercise. Conversely, if we find a significant impact, the impact of the Metrocable identified previously contains influences from sources that were not the intervention. Table 10 shows the principal results of the placebo test, both the traditional and spatial difference-in-differences results, and those for the short and medium run for treated units and their first-, second-, and third-order neighbors. Although some significance is captured for the treatment model, we should recall that we have few units in this model and results on that spectrum are somewhat noisy. Therefore, we can infer that there is no strong evidence that the placebo Metrocable is responsible for variations in the homicide rate in that area of the city.

Figure 5: Placebo treatment assignment



Source: author's calculation
Note: the location of the fake Metrocable was chosen according to the terrain's slope, which is similar to the slope of the real Metrocable. Additionally, the distance between stations is the same as that of the real one and of the complete length of the Metrocable.

Appendix D Other Crimes

We repeat the main exercise for other types of crimes that we have information: auto theft and theft to commercial establishments. In order to understand the possible links between the investment in the Metrocable and these types of crime, we need to come back to the basic relationship between homicides and the Metrocable. Compare to other countries where homicides are mainly related to personal reasons, in Colombia the presence of illegal groups and the influence of the drug cartels have made homicides a business for low income people.

The results we have documented are related to economic and criminal incentives related to the Metrocable transportation system. The investments done through the Metrocable improved low income households' accesibility to the rest of the city, including labor markets across town. It also decreased the cost of public transportation for those households. The presence of police and the improvement in the street network increased the efficiency of police to deter crime.

Table 11 shows the results for auto theft and thefts to establishments. In the case of auto theft, we observe positive impacts in the short-run, which does not seem surprising since auto theft depends on the availability of automobiles in the area. After the improvement in the street network and the accesilibilty of the treated neighborhoods to the rest of the city, it is expected that more cars will be able to transit in the area and this could explain the positive effects in the short-run. To further support this, the effects found in the medium run are negative, suggesting that the implementation of the Metrocable also reduces the level of auto theft in the treated plus second and third neighbors. The effects are smaller that those found for homicides, but they are increasing in absolute values as one includes more neighbors suggesting similar behaviour to the one of homicides.

The bottom panel of Table 11 shows the results for thefts to commercial establishments, which in conclusion provide no evidence of positive or negative effect of the Metrocable in the level of thefts in the short- or medium-run. One reason why there is no clear effect of the Metrocable on thefts to commerce is that the different mechanisms work in opposite directions. The improvement conditions of the neighborhoods would led to increase commercial activity and not surprisingly increases in thefts to stores. However, the increase in police presence would deter some criminal activity against commercial establishments. Then, the final impact is ambiguous and in this case there is no evidence of a final impact. Another challenge of using the variable of thefts is the level of underreporting in the city. In Colombia, crimes related to theft are usually not reported to the police unless the property stolen is highly valuable and there is not immediate danger of retaliation to the owners by the perpetrators.

Trying to disentangle the mechanisms behind the effects found on those types of crimes is much harder than the case of homicides. One of the assumptions to identify the mechanisms behind the effect of homicides is that captures not related to homicides can be considered as a measure of police efficiency that is affected by the treatment but not directly by the number of homicides. This relies on the fact that homicides' offenders respond more to criminal investigations than just police presence, which is not the case for auto theft and other types of theft.

Table 7: Summary statistics for the city and for the analytical regions (Treated+1st Neighbors)

Variable	Observations	Statistic	Year 2004	Year 2006	Year 2012
City data					
Homicides per 100,000			50.51	35.91	52.28
Captures per 100,000			315.03	212.33	225.57
% workers without retirement			70.39%	60.22%	42.95%
Average labor income			$667,107	$542,474	$929,615
% Married			24.68%	24.50%	23.97%
% Youth 15-19 not in school			31.84%	28.17%	28.17%
% Secondary education			45.51%	41.01%	39.67%
Treated+1st Neighbors					
Homicides per 100,000	17	Mean	54.18	20.58	25.97
Homicides per 100,000	17	Std. Dev.	28.53	22.93	23.77
Homicides per 100,000	17	Median	51.08	13.15	16.42
Captures per 100,000	17	Mean	194.28	72.65	118.63
Captures per 100,000	17	Std. Dev.	74.20	53.88	69.32
Captures per 100,000	17	Median	173.31	76.42	99.71
% workers without retirement	17	Mean	77.36%	74.97%	58.76%
% workers without retirement	17	Std. Dev.	7.77%	10.40%	7.77%
% workers without retirement	17	Median	78.80%	75.92%	59.94%
Average labor income	17	Mean	$393,935	$386,661	$482,469
Average labor income	17	Std. Dev.	$46,474	$52,504	$48,231
Average labor income	17	Median	$395,443	$360,634	$479,387
No treated					
Homicides per 100,000	159	Mean	58.56	35.41	51.57
Homicides per 100,000	159	Std. Dev.	111.57	42.58	61.88
Homicides per 100,000	159	Median	36.88	26.14	36.15
Captures per 100,000	159	Mean	505.94	253.90	305.05
Captures per 100,000	159	Std. Dev.	1726.42	888.07	700.51
Captures per 100,000	159	Median	217.66	91.10	155.97
% workers without retirement	159	Mean	69.35%	58.25%	40.83%
% workers without retirement	159	Std. Dev.	13.79%	13.54%	15.14%
% workers without retirement	159	Median	70.12%	56.89%	42.07%
Average labor income	159	Mean	$789,289	$582,321	$1,000,106
Average labor income	159	Std. Dev.	$582,971	$363,935	$736,281
Average labor income	159	Median	$577,223	$475,269	$710,941

Source: author's calculation
Note: complete summary statistics are available upon request.

Table 8: 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, drug-related, manslaughter and homicide
$Cap^{(3)}$	**Terrorism**, drug-related, manslaughter and homicide
$Cap^{(4)}$	**Drug-related crimes**, manslaughter and homicide
$Cap^{(5)}$	**Manslaughter** and homicide
$Cap^{(6)}$	**Homicide**
Total	**None**

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

Table 9: Direct, Indirect, and Total impacts of the Spatial Durbin Model: Monthly

	1st Neighbors		*2nd Neighbors*		*3rd Neighbors*	
Effect Treatment ($t_0 - 2006m12$)						
Direct	-0.064		-0.156		-0.204	*
	(0.16)		(0.11)		(0.11)	
Indirect	-0.431	*	-0.528	***	-0.682	***
	(0.24)		(0.16)		(0.23)	
Total	-0.495	***	-0.684	***	-0.886	***
	(0.16)		(0.17)		(0.24)	
Rho	0.037	***	0.112	***	0.138	***
	(0.01)		(0.02)		(0.03)	
Direct Effect Treatment broken down by time						
0-5 Months after	-0.056		-0.073		-0.084	
	(0.09)		(0.06)		(0.05)	
6-11 Months after	-0.153		-0.134	***	-0.147	***
	(0.11)		(0.05)		(0.04)	
12-17 Months after	-0.046		-0.100		-0.136	
	(0.11)		(0.09)		(0.08)	
6 month prior	-0.142		-0.107		-0.102	
	(0.10)		(0.08)		(0.07)	
Indirect Effect Treatment broken down by time						
0-5 Months after	-0.084		-0.106		-0.123	
	(0.14)		(0.17)		(0.22)	
6-11 Months after	-0.055		-0.217		-0.346	**
	(0.20)		(0.15)		(0.17)	
12-17 Months after	-0.253	**	-0.323	***	-0.361	*
	(0.12)		(0.12)		(0.19)	
6 month prior	0.085		0.021		0.008	
	(0.12)		(0.17)		(0.22)	
Total Effect Treatment broken down by time						
0-5 Months after	-0.139	*	-0.179		-0.207	
	(0.08)		(0.13)		(0.20)	
6-11 Months after	-0.208	*	-0.350	***	-0.493	***
	(0.12)		(0.14)		(0.16)	
12-17 Months after	-0.299	***	-0.423	***	-0.497	***
	(0.10)		(0.12)		(0.19)	
6 month prior	-0.057		-0.085		-0.094	
	(0.08)		(0.14)		(0.21)	

Source: Author's calculation.
Note:$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Models include time and neighborhoods fixed effects. Errors are clustered at the neighborhood level.

Table 10: Placebo test, conducted by creating a fake Metrocable line

Dependent: ln(Homicides+1)	**Treated**		**Treated + 1st Neighbors**		**Treated + 2nd Neighbors**	**Treated + 3rd Neighbors**
Difference-in-Differences						
			Short Impact (2004-2006)			
Total Impact	-0.477		-0.172		-0.123	-0.218
	(0.42)		(0.34)		(0.26)	(0.20)
	-37.95%		-15.82%		-11.54%	-19.56%
			Medium Impact (2004-2012)			
Total Impact	-0.661	**	-0.441		-0.312	-0.203
	(0.30)		(0.29)		(0.24)	(0.18)
	-48.35%		-35.65%		-26.81%	-18.33%
Spatial Difference-in-Differences						
			Short Impact (2004-2006)			
Total Impact	-0.524		-0.180		-0.129	-0.217
	(0.36)		(0.30)		(0.24)	(0.19)
	-40.79%		-16.50%		-12.14%	-19.54%
			Medium Impact (2004-2012)			
Total Impact	-0.639	**	-0.462	*	-0.340	-0.222
	(0.30)		(0.27)		(0.23)	(0.18)
	-47.23%		-37.01%		-28.79%	-19.93%
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 terrain's slope, which is similar to the slope of the real Metrocable. Additionally, the distance between stations is the same as that of the real one and of the complete length of the Metrocable.

Table 11: Spatial DiD for other types of crimes

Dependent:	**Treated**		**Treated + 1st Neighbors**		**Treated + 2nd Neighbors**		**Treated + 3rd Neighbors**	
ln(Auto Theft+1)								
			Short Impact (2004-2006)					
Total Impact	-0.502		0.318		0.502	**	0.477	**
	(0.35)		(0.30)		(0.25)		(0.21)	
	-39.50%		37.44%		65.17%		61.05%	
			Medium Impact (2004-2012)					
Total Impact	-0.199		-0.278		-0.433	*	-0.518	**
	(0.28)		(0.25)		(0.25)		(0.22)	
	-18.08%		-24.28%		-35.13%		-40.44%	
ln(Theft to Establishments+1)								
			Short Impact (2004-2006)					
Total Impact	-0.058		0.060		0.217		0.176	
	(0.57)		(0.35)		(0.29)		(0.25)	
	-5.61%		6.20%		24.27%		19.23%	
			Medium Impact (2004-2012)					
Total Impact	-0.065		0.074		0.103		0.269	
	(0.54)		(0.33)		(0.28)		(0.23)	
	-6.32%		7.68%		10.80%		30.81%	
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. The unit of analysis is the analytical region.