BORRADORES DE ECONOMÍA

Spatial Mobility, Economic Opportunity, and Crime

By: Gaurav Khanna
Carlos Medina
Anant Nyshadham
Daniel Ramos-Menchelli
Jorge Tamayo
Audrey Tiew

Núm. 1334
Dec. 2025

BANCO DE LA REPÚBLICA COLOMBIA

Spatial Mobility, Economic Opportunity, and Crime

Gaurav Khanna, Carlos Medina, Anant Nyshadham
Daniel Ramos-Menchelli, Jorge Tamayo, Audrey Tiew*

Abstract

Neighborhoods are strong determinants of both economic opportunity and criminal activity. Does improving connectedness between segregated and unequal parts of a city predominantly import opportunity or export crime? We use a spatial general equilibrium framework to model individual decisions of where to work and whether to engage in criminal activity, with spillovers across the criminal and legitimate sectors. We match at the individual level various sources of administrative records from Medellín, Colombia, to construct a novel, granular dataset recording the origin and destination of both workers and criminals. We leverage the rollout of a cable car in an event study design, and show how access to transit lines reduces criminal participation and induces legitimate employment. We identify key parameters of the model, informing how changes in transportation costs causally affect the location and sector choices of workers and criminals. Our counterfactual exercises indicate that, when improving the connectedness of neighborhoods, overall criminal activity in the city is reduced, and total welfare is improved.

Keywords: *urban transit infrastructure, crime, Medellín, spatial equilibrium*
JEL Codes: F14, J24, J46, K42, O17, R40

*Khanna: University of California- San Diego; Medina: Banco de la República de Colombia, Medellín; Nyshadham: University of Michigan, Good Business Lab, BREAD, JPAL & NBER; Ramos-Menchelli: Johns Hopkins, SAIS; Tiew: New York University; Tamayo: Harvard Business School, Digital Reskilling Lab - The Digital, Data, and Design Institute at Harvard. The opinions expressed herein belong to the authors and do not necessarily reflect the views of Banco de la República or its Board of Directors. We thank Cristian Chica, David Bernal, Nicolás Torres, and Santiago Velásquez for excellent research assistance. We thank Luz Dary Botero Ramírez and the team of Strategic Planning at the *Metro de Medellín*, and Olga María Ospina at the Chamber of Commerce of Medellín for sharing detailed information. We thank Juan Carlos Duque, Juan Carlos Munoz, and Arantxa Rodriguez-Uribe, for sharing valuable data. We appreciate detailed comments from Pol Antras, Arnaud Costinot, Dave Donaldson, Ed Glaeser, Gordon Hanson, Gabriel Kreindler, Amine Ouazad, Evan Rose, Esteban Rossi-Hansberg, Nicolas de Roux, Micaela Sviatschi, Santiago Tobón, Nick Tsivanidis, Juan Sebastián Vélez, and Roman D Zárate.

Movilidad espacial, oportunidad económica, y crimen

Gaurav Khanna, Carlos Medina, Anant Nyshadham
Daniel Ramos-Menchelli, Jorge Tamayo, Audrey Tiew*

Resumen

Los vecindarios son importantes determinantes tanto de las oportunidades económicas como de la actividad criminal. Mejorar la conectividad de vecindarios segregados y pobres, con el resto de la ciudad, importará oportunidades a esos vecindarios, o exportará crimen desde ellos? Nosotros utilizamos un modelo de equilibrio general para modelar las decisiones individuales de dónde trabajar y de si involucrarse en actividades criminales, incorporando efectos sobre los sectores criminal y legal. Construimos una novedosa base de datos a nivel individual con base en varios registros administrativos de Medellín, Colombia, que incluye el origen y el destino tanto de los empleados como de los criminales. Nosotros aprovechamos la construcción de varias líneas de cable del Metro de Medellín, y mostramos cómo el acceso a las estaciones conectadas por estos cables reduce la participación en actividades criminales e incrementa el empleo formal. También identificamos varios parámetros del modelo que nos permiten estimar, cómo los cambios en los costos del transporte, afectan de forma causal, la ubicación y la elección sectorial, de empleados y criminales. Nuestro ejercicio contrafactual indica que, cuando se mejora la conectividad de los vecindarios, la criminalidad total de la ciudad se reduce, y el bienestar total se incrementa.

Palabras claves: *Infraestructura de transporte urbano, crimen, Medellín, equilibrio espacial.*
Códigos JEL: F14, J24, J46, K42, O17, R40.

* Khanna: University of California-San Diego, gakhanna@ucsd.edu; Medina: Banco de la República de Colombia, Medellín, cmedindu@banrep.gov.co; Nyshadham: University of Michigan, Good Business Lab, BREAD, JPAL & NBER, nyshadha@umich.edu; Ramos-Menchelli: Johns Hopkins, SAIS, danielramos@jhu.edu; Tiew: New York University, audreytiew@nyu.edu; Tamayo: Harvard Business School, Digital Reskilling Lab - The Digital, Data, and Design Institute at Harvard, jtamayo@hbs.edu.

1 Introduction

Income, economic opportunity, and criminal activity are all unequally spatially distributed in cities across the world (Athey et al., 2020; Blattman et al., 2022; Cutler and Glaeser, 1997; Davis et al., 2019). Neighborhood segregation is often both the cause and consequence of the interplay between legitimate and illegitimate activity (Card et al., 2008). As a result of segregation, neighborhoods are often strong predictors of both economic opportunity and criminal activity (Chyn, 2018; DiTella et al., 2010; Jacob, 2004; Kling et al., 2007; Melnikov et al., 2022).

Canonical models of crime (Becker, 1968; Ehrlich, 1973) often depict criminal activity as a rational choice in the face of limited legitimate economic alternatives. Such frameworks would suggest that investing in transit infrastructure, to better connect low-income populations segregated from opportunity to more economically active parts of the city, could reduce criminal participation. Yet, cities across the world have been resistant to such transit expansions, with the concern that crime could spread to more affluent victims and properties, as potential perpetrators obtain access to more neighborhoods.[1] We investigate these claims by asking: Does improving connectedness between segregated and economically unequal parts of a city predominantly import legitimate opportunities as an alternative to criminal activity or export crime to other parts of the city?

Empirically evaluating the consequences of transportation investments on both localized and aggregate income, employment, and crime is, however, difficult as these are jointly determined in spatial equilibrium. All parts of the city are theoretically affected in some way by even localized infrastructure expansions, making 'control groups' for comparison elusive. This issue is exacerbated by the possibility of externalities across sectors and neighborhoods, and the occurrence of neighborhood-specific shocks (like gang wars and changes to policing) that may coincide in time and space with expansions in public infrastructure. We build on recent developments in economic geography to construct a framework that includes both legitimate and criminal employment and allows for spillovers across these sectors (Ahlfeldt et al., 2015; Donaldson, 2018; Donaldson and Hornbeck, 2016a; Tsivanidis, 2023; Zárate, 2023).

[1]See, for instance, the examples of Atlanta "The Myth That Mass Transit Attracts Crime Is Alive in Atlanta" in Bloomberg (Dec, 2014), and Baltimore "'Addicts, crooks, thieves': the campaign to kill Baltimore's light rail" in the Guardian (Aug, 2018). Indeed, there is no shortage of events from around the world to evaluate the impacts of improving transportation connectedness on income distortion, and both localized and aggregate crime. Most major cities in the world over the last century have faced perceived trade-offs like these when making decisions on whether to invest in expanding transportation by linking prosperous, affluent areas to struggling neighborhoods.

Yet, credibly estimating the parameters of the model raises a second set of challenges, as it requires detailed, granular data and reliable variation for identification. We leverage the rollout of a public transit system over a decade to identify parameters. However, to do so, we need exceedingly rare data on the flows of workers and crime from origin to destination. That is, over the period, we need to know where individuals live, where they engage in legitimate work, and where they travel to commit crimes. Having such data allows for transparent identification of parameters, and a tractable reduced-form analysis that does not rest heavily on the model structure.

We use the universe of geocoded arrests over more than a decade in Medellín, Colombia, matched to individual-level administrative records on employment and home addresses from repeated household-level censuses of the poor. We further combine these with employer-employee matched data, which document the location of firms and individual monthly wages. These matched individual-level administrative data allow us to estimate the impacts of several expansions in transportation infrastructure on the level and spatial distribution of income, employment, and crime. We combine this with additional data on commuting surveys, land registries, house prices, and the location of informal establishments to complete the analysis.

Medellín offers an ideal setting in which to study the spatial diffusion of crime and prosperity in that it was, during our time of study, one of the most violent cities in the world and starkly exhibited the spatial heterogeneity in crime rates and segregation from economic opportunity characteristic of most major urban centers. In this way, Medellín mirrors both major cities from developing regions like Latin America, as well as recent histories of many large cities in developed countries like New York, Los Angeles, and Chicago. Medellín also experienced several expansions of the metro cable transportation system during our study period by which previously disconnected poor neighborhoods with varying degrees of baseline criminality became linked to both high-crime areas and high-opportunity, low-crime areas.

We start by documenting comprehensive reduced-form evidence that these expansions decreased the likelihood that inhabitants of high-crime neighborhoods near the newly built stations were arrested for crimes. Importantly, lower commute times predict higher legitimate employment, earnings, and housing values. Event study analyses suggest that inhabitants of segregated neighborhoods, indeed, seemed to take advantage of new opportunities, as new cable lines improved access. These patterns are robust to various specifications and controls, leveraging variation from incidentally connected neighborhoods, and instrumental variables derived from engineering costs.

In complementary pairwise-neighborhood gravity regressions, we estimate the elasticity of commuting flows to commute times, by type of activity, and find that those engaged in crime are more sensitive to commute times. We further leverage the granularity of our data to distinguish between sorting across neighborhoods and the occupational choice of residents. Using individual-level regressions, we find that in the longer run, residents of neighborhoods change the activities they are likely engaged in. How these patterns on commuting sensitivity, neighborhood choice, and occupational choice affect aggregate criminal activity and welfare requires a quantitative model framework.

Indeed, our empirical patterns exhibit stark heterogeneity by the baseline spatial distribution of economic opportunity and crime in newly connected neighborhoods. The reductions in criminal participation are strongest in areas that were originally high-crime and segregated from legitimate economic opportunity, while some low-crime neighborhoods near the newly built stations even experienced (smaller) increases in criminal activity. These heterogeneous and countervailing effects emphasize the importance of modeling and jointly estimating the employment decisions of individuals across both sectors and space under different travel cost regimes.

Accordingly, we develop a spatial equilibrium model with both legitimate and criminal employment sectors drawing from recent studies (Ahlfeldt et al., 2015; Tsivanidis, 2023; Zárate, 2023), and estimate the effects of several transportation expansions on the equilibrium level and spatial distribution of employment and crime. This framework allows us to address SUTVA violations,[2] account for correlated neighborhood-level shocks when identifying parameters, and capture the rich heterogeneity in baseline access to different types of opportunities. In doing so, the model also allows for rich analysis of policy counterfactuals, including the decomposition of how crime externalities affect welfare via sector choice or changes in commuting patterns.

We build on previous models in two important ways. First, we incorporate the role of crime, modeling individuals' sectoral choice (between crime and legitimate employment). Crime is unlike other forms of economic activity, as it affects both the functioning of legitimate businesses and neighborhood amenities. So, our second innovation draws inspiration from recent studies of externalities in spatial models (Bryan et al., 2020; Rossi-Hansberg et al., 2010), to allow for inter-sectoral spillovers. Crime may have negative externalities on other forms of economic activity and residential amenities. Yet, new legitimate economic activity changes the returns to crime, and potentially has consequences for economic agglomeration. We identify crime externalities by de-

[2]The Stable Unit Treatment Value Assumption is violated as all neighborhoods are indirectly affected by new transit lines.

riving variation from other sources, such as the onset of gang wars as a result of the extradition of drug lords to the US.[3]

As mentioned above, a major strength of this framework is that it allows us to conduct various counterfactual exercises with alternative degrees and directions of expansion of the transportation infrastructure. These exercises allow us to answer several important questions. How do improvements in transportation infrastructure affect occupational choice? Does connecting poor neighborhoods to more employment opportunities predominantly import opportunity or export crime? Which neighborhoods should we target for further expansions in transit access? What are the resulting net effects on aggregate crime and welfare, as well as inequality across neighborhoods? What channels drive changes in welfare for different types of neighborhoods? These questions are at the heart of policy debates in nearly every city in the world surrounding whether and in which directions to expand public transportation infrastructure.

We simulate new cable lines that were only recently built. We find that newly connected areas see a sharp reduction in individuals engaging in criminal activity. When low-opportunity areas are connected to legitimate work in other parts of the city, individuals are more likely to switch away from crime. Larger reductions in commute times lead to larger reductions in criminality. As such, neighborhood segregation appears to be a meaningful driver of aggregate crime and welfare in the city.

While these cable lines predominantly led to an 'import of opportunity,' and so a reduction in aggregate crime rates, we do find that there was also a corresponding 'export of crime.' That is, the destinations where criminal activity occurred spread to other neighborhoods. The 'export of crime' to other parts of the city, may explain why affluent neighborhoods in many parts of the world have tried to block transportation expansions. Indeed, crime externalities play a meaningful role in overall welfare, predominantly mediated through the role of sector choice ('import of opportunity'). More than 30% of the overall welfare changes in newly-built transit lines result from sector-choice-driven reductions in criminal externalities.

To better understand which neighborhoods policy-makers should target for transit expansions, we perform counterfactuals in which we reduce transportation costs to the rest of the city by 10% for each neighborhood in turn. Despite crime being 'exported' to certain other parts of the city, greater connectedness for all, but some of the highest baseline legitimate-sector market access neighborhoods, yields aggregate reductions in crime, and increases in welfare. The largest gains accrue when connecting

[3]The extradition of gang lords leads to turf wars in neighborhoods under the extradited kingpin. This increase in crime can then be used to estimate the impacts of firm productivity and residential amenities.

neighborhoods with the lowest legitimate-sector market access at baseline. In a handful of neighborhoods, reductions in transportation costs raise aggregate crime levels, and lower productivity. Once again, crime externalities play an important role: sector choice improves welfare in the least-connected neighborhood, while changes in commuting and residential patterns display wide variation in their contribution to welfare.

Our work speaks to four distinct literatures. First, our results contribute to the crime literature on the link between employment opportunities and criminality (Becker, 1968).[4] Our study is closest to recent work by Blattman et al. (2022) and Sviatschi (2022), which documents that criminal productivity varies across neighborhoods in cities and regions of countries, leading to long-lasting spatial patterns in criminal and legitimate economic activity. We embed this critical insight into a spatial equilibrium commuting model with criminal and legitimate sectors. Over and above comparisons across neighborhoods, we examine how transportation infrastructure investments connecting previously segregated areas of criminal and legitimate economic activity affect both the spatial distribution and aggregate city-level criminality.

Second, we contribute to recent work developing spatial equilibrium models by adapting these models and methods to the study of criminal activity (Ahlfeldt et al., 2015; Donaldson, 2018; Donaldson and Hornbeck, 2016a). Our study is closest to recent work by Tsivanidis (2023) and Zárate (2023). Our model builds on innovations in these previous influential studies to allow for spillovers across legitimate and criminal sectors: crime affects neighborhood amenities and firm productivity, and legitimate sector activity affects returns to criminality and agglomeration. These externalities generate nuanced dynamics, whereby reductions in transit costs may not always be beneficial, and in certain instances, can increase aggregate crime and lower productivity. Our methods allow us to decompose the contributions of various drivers of criminal externality, such as the changes in occupations, commuting patterns, and residential choice.

Next, we speak to work on the relationship between public transit and crime, which documents short-run responses to station closures or strikes (David C. and Danielle, 2015; Greg and John M., 2017), and the heterogeneity in impacts across neighborhood characteristics (Billings and Burkardt, 2011; Cerdá et al., 2012; Ihlanfeldt, 2007). Building on this evidence, our analysis is a long-run spatial general equilibrium analysis for the entire city. Opening a new station does not just affect neighborhoods near the station, but those further away as well, especially in the longer term, as individ-

[4] Prior related studies have validated this link, using variation from trade shocks (Dell et al., 2019; Dix-Carneiro et al., 2018), job loss (Bennett and Ouazad, 2018; Britto et al., 2022; Khanna et al., 2021; Rose, 2020), and public policies (Fu and Wolpin, 2017; Khanna et al., 2023).

uals change their occupations, where they work, and where they live. Indeed, sector choice is an important driver of overall welfare, particularly as aggregate reductions in criminality lower adverse externalities on legitimate sector production.

Finally, we build on recent evidence on residential and 'experienced' segregation (Athey et al., 2020) or 'consumption segregation' (Davis et al., 2019) in the urban economics literature. Perhaps, closest to our study, is recent work by Melnikov et al. (2022), which shows that restricted movement out of criminal enclaves has lasting impacts on the economic development of those areas and their residents. We document that reducing 'employment segregation' by linking poor, marginalized neighborhoods to employment opportunities in distant parts of the city can have profound impacts on criminal activity. Our paper is the first to our knowledge to study criminal participation in a quantitative spatial equilibrium framework as transportation costs and returns to both legal work and crime change across neighborhoods.

2 Data

A comprehensive causal analysis of how the geography of crime and legitimate employment change in response to transit networks requires new data that had to be assembled for this project. We need detailed information on where individuals live, where they work, and where they commit crimes over time. The richness of these data allows us to estimate spatially granular models used in urban economics, with multiple sectors, including criminality. Details on the data are in Appendix A.

We combine administrative data on households, jobs, crime, commuting times, and house prices from various sources. We link individual records using government-issued individual identification numbers and dates of birth. Since we leverage identification from changes to neighborhood access, we treat the neighborhood as the primary geographic unit. There are 269 neighborhoods with an average size of 373 thousand square meters, and 7,756 inhabitants.[5]

The first source of data are from three waves of the *Sistema de Selección de Beneficiarios para Programas Sociales* (SISBEN I, SISBEN II and SISBEN III, System for the Identification of Potential Beneficiaries of Social Programs) from the Department of National Planning (2015). SISBEN I (2002), SISBEN II (2005), and SISBEN III (2010) allow us to track individuals, their households, and residential locations over time. The SISBEN waves are Censuses of the poor, covering approximately 65-75% of the house-

[5]While possible to conduct the analysis at a more disaggregated block level, one may be concerned about making the data too granular (Dingel and Tintelnot, 2020). Since we have many inhabitants per neighborhood, we use the neighborhood as our unit of observation.

holds in the city, classified into six different socio-economic levels according to the SISBEN score. They include a rich set of demographic information, type of work activity (whether formal or informal), assets and income, and access to various government programs. Importantly, these data allow us to identify the location of the residence of individuals in Medellín, and track their changes in residences over time.

The second data source, from the *Seccional de Investigación Judicial del Area metropolitana del Valle de Aburrá* (Judicial Research Unit of the Metropolitan Police of the Aburrá Valley, 2016), is the census of arrests in Medellín between 2002-15, regardless of conviction. These data contain information on the type of crime committed, the date and neighborhood of the crime, and the arrested individual's unique identification number. The data also has the specific Act in the penal code that the individual was charged with, allowing one to classify the different types of crime. We classify crimes into three categories – violent, property, and drug crimes – based on the US Bureau of Justice Statistics' classifications in the Sourcebook of Criminal Justice Statistics (BJS, 1994). We also use neighborhood-level aggregated crime statistics from 2003 to 2018.

Third, we use the *Sistema Integral de Protección Social* (SISPRO, System for Social Protection), which contains information from the *Planilla Integrada de Liquidación de Aportes* (PILA, Integrated Register of Contributions) for all formal workers contributing to health and pension schemes (Ministry of Health, 2019). The PILA has detailed payroll information, earnings, days worked, firm and worker identifiers, and demographics. This measures who is engaged in formal work, and how much they earn.

To determine workplace locations, we use the *Camara de Comercio de Medellin* (Chamber of Commerce of Medellin), a census of all firms formally registered with the Medellín government between 2007 and 2018. This contains identification numbers of statutory representatives, reported total assets and liabilities, and, most importantly, establishment addresses. We complement this with information on the number of informal establishments at the destination from Straulino et al. (2022).[6]

We link individual identification numbers from formal employment and criminal arrest records with neighborhood-of-residence data from SISBEN to construct origin–destination commute flows within the city. This linkage allows us to observe and compare commuting patterns of formal and criminal workers across neighborhoods.

We augment these data with the *Encuesta de Calidad de Vida* (Medellin's household survey) from 2004 to 2018 which report household information about number of

[6]Given that PILA and *Camara de Comercio* capture only formal employment, we supplement it with data from the population Census of 2005 (Encuesta de Calidad de Vida), informality rates from SISBEN, as well as data from Straulino et al. (2022) to approximate total legitimate activity (formal and informal) when needed for counterfactual analysis. Details are provided in Appendix A.2.

workers (formal and informal), income, and house rental rates; and the Land Registry Data from Medellin's Cadastre from 2013 to 2019 which reports the use, floorspace, and land area, value per square meter of land and floorspace, as well as a number of property characteristics. Finally, we obtain microdata on commuting behavior from regular transportation surveys that measure commute times, mode of transportation, and the location of origin and destinations for each trip, over this period.

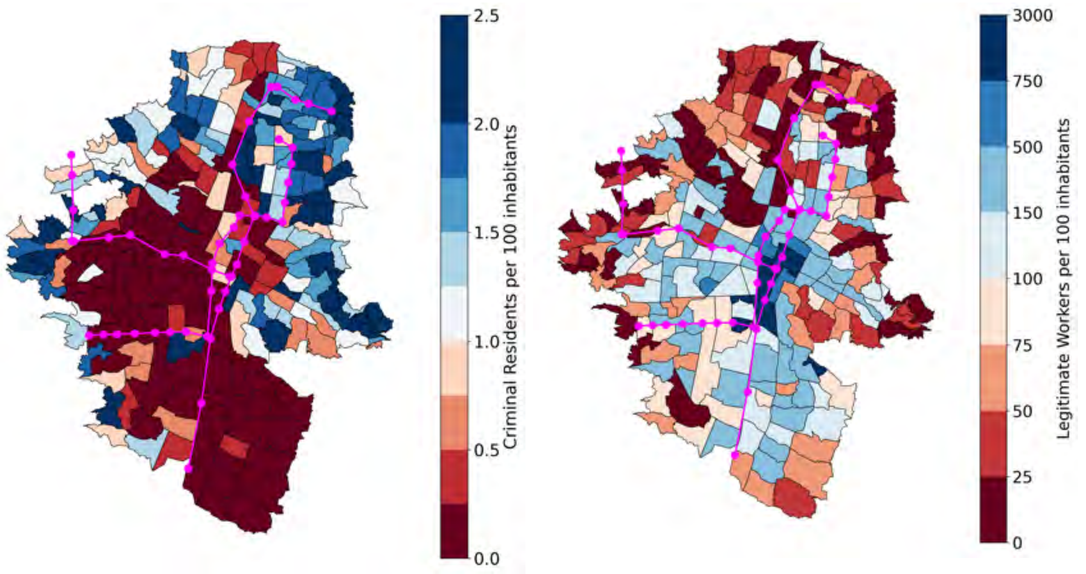
We use GIS information on the location of public transport stations and the road network in Medellin to construct historical commute times for public transport and cars. We do so using the Network Analysis toolkit from ArcGIS, which also allows us to build counterfactual commute times that we use in the model.[7]

3 Neighborhoods, Commuting, and Crime in Medellín

3.1 Segregation and Urban Transit in Medellín

Figure 1: Segregation in Crime and Legitimate Employment by Neighborhood, 2010

(a) Criminal Residents per 100 inhabitants (b) Legitimate Employment per 100 inhabitants



Note: Spatial distribution of where individuals arrested in 2010 reside (left panel), and where individuals in 2010 work (right panel). Dotted lines show the transit lines in 2010. Data are aggregated to the neighborhood level.

Located in northwestern Colombia, Medellín is the second largest city after the capital, Bogotá. It has strong industrial and financial sectors with approximately 2.7

[7]We describe the construction of the transport network in Section A.3 of the Appendix.

million people or 5.1% of Colombia's population. The urban zone comprises 269 neighborhoods, divided into 21 *comunas*, 5 of which are semi-rural township *corregimientos*.

The city is starkly segregated in terms of where individuals live, work, and where criminal activity is prevalent. Figure 1 describes the spatial distribution of criminal activity and legitimate employment across the city in 2010, along with transit lines that existed in 2010. Those involved in the crime live in areas that were historically associated with drug cartels. These include the northeast, the western edge of the city, and the eastern extremity. There are also pockets of crime near downtown: the city center, where the transit lines intersect. Crime is notably low in the affluent southeastern edge of the city, and for much of the western part of the city.

While criminal participation is more prevalent around the edges of the city, economic activity is starkly present in the central downtown, and smaller business districts around the center. There are also pockets of activity in each of the different quadrants of the city.

Before the roll-out of the cable car system in Medellín, most commuting relied on a single North-South metro line running through the heart of the city, at the bottom of the valley. The city displays significant elevation when moving either east or west from this central line. To expand the transit infrastructure, therefore, simple metro lines were infeasible and costly. As a result, the transit network that emerged relied on cable cars that traversed up the slopes of the hills, and over the residences of the city.

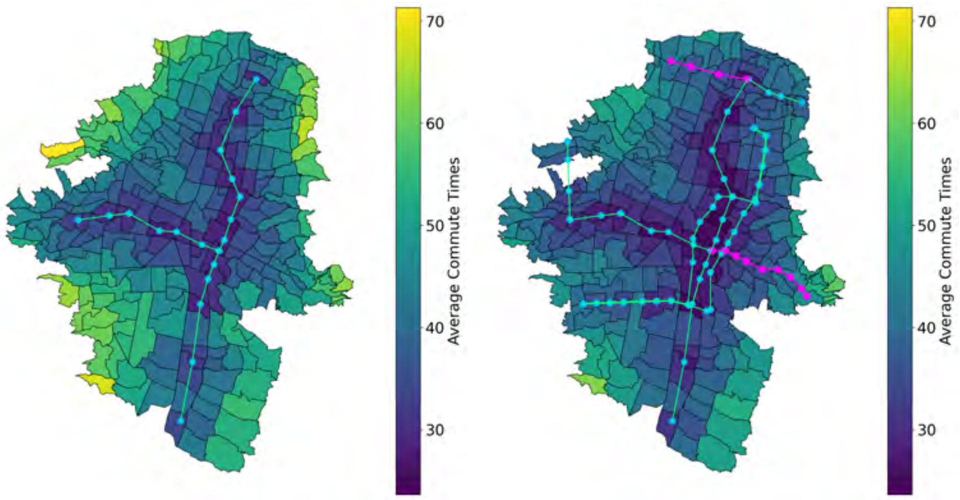
Over our sample period, cable lines were built in 2004 (Linea K, northeast) and 2008 (Linea J, west), tramways in 2015 (Linea T, east), multiple large Bus Rapid Transit (BRT) corridors starting in 2012, and a cable in 2021 (Linea P, northwest). Figure 2 describes the roll-out of the transit infrastructure over the course of our analysis period, particularly demarcating the lines we use for out-of-sample counterfactual exercises. We also include the average commute times to different parts of the city, where lighter shades are longer commute times.[8]

Figure 2 shows how, over the period, as new transit lines were added, the average commute times to various neighborhoods fell substantially, improving access to other parts of the city. For instance, consider the cable line that was built on the northeastern edge of the city in 2004. These neighborhoods, traditionally had high crime, and displayed relatively high commute times to other parts of the city, perhaps limiting access to opportunity. After 2004, when the cable line was built, there was a sharp drop in commute times in the newly connected neighborhoods.

[8]See Appendix, A.3 for details on the construction of commute times.

Figure 2: Roll out of Transit Lines and Change in Commute Times, 2002-2021

(a) Commute Times and Transit, 2002 (b) Commute Times and Transit, 2021



Note: Average commute times originating from neighborhoods in 2002 (left panel) and 2021 (right panel). Between the two years, metro cable and tram lines were built, reducing average commute times in neighborhoods. Lighter shades represent longer commutes. The data are aggregated to the neighborhood-level. The pink lines in the northwest and eastern represent lines we perform counterfactual exercises on, and do not use for estimation. Commute times are constructed as explained in Appendix A.3.

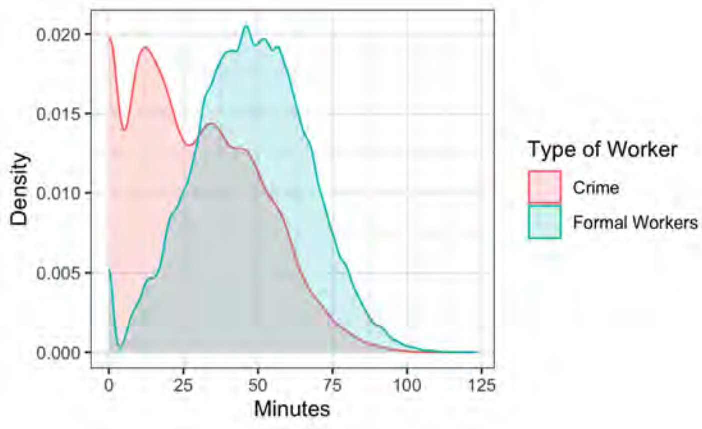
3.2 Commute Times for Different Activities

Consider Figure 3 that plots the commute times in our individual-level data for different types of criminal activity and for formal work. It shows that formal workers travel far to access their jobs, many more than an hour. In contrast, most crime is committed near where the perpetrator of the crime resides. This is consistent with the fact that most crime in Medellín is localized, and often tied to local street gangs (*combos*), that oversee most criminal activity (Blattman et al., 2018). This is true of not only low-level crimes like petty theft, but also drug trafficking and violent crime.[9]

The differences in commute times have meaningful implications for what would happen when new transit lines are built. On the one hand, the raw densities may suggest that criminal activity is more sensitive to commute times than formal work. If so, changes to commute times may have a sharper effect on the spatial distribution of crime than on legitimate-sector employment. On the other hand, the densities may indicate that legitimate work is strongly segregated and confined to certain pockets, and reaching those pockets requires a fair amount of commute time. New transit lines

[9]The Criminology literature has documented that crime tends to be highly localized (Capone and Nichols Jr, 1976; Georges-Abeyie and Harries, 1980). We are the first to study the implications of these differences in commute elasticities across sectors for city-level outcomes.

Figure 3: Kernel Density of Commute Time by Activity, 2010



Note: Commute times by activity in 2010. We measure the origin (residence) of individuals, and the destination of their activity (formal work and crime). We use road maps, transit networks, and travel times by different modes of transport to estimate commute times for each origin-destination pair; see Appendix A.3. We restrict our data to 1 individual per observation; i.e., for crime, the first arrest in 2010.

that reduce these commute times increase access to these pockets of legitimate-sector opportunities, and may induce individuals-on-the-margin away from crime, which dominates the opportunity set when search is restricted to areas close to home. This latter implication of segregation is consistent with the maps shown in Figure 1.

3.3 Crime in Medellín

Violence in Colombia has traditionally been high. The emergence of drug cartels in the late 1970s and early 1980s, fueled the emergence of organized crime to support illegal businesses, and guerrilla or paramilitary groups to care for the entire production chain. From the mid-1980s to the early 1990s, homicide rates rose, rapidly driven by cartels, paramilitaries, and local gangs. Medellín used to be one of the most violent cities in the world (see Figure D.1 from CCSPJP (2009)). The high crime rates reflect the presence of urban militias, local gangs, drug cartels, criminal bands, and paramilitaries.[10] Many demobilized militias continue to be involved in crimes like extortion and trafficking, given their experience with using guns and avoiding police (Rozema, 2018).

Homicide rates in the city peaked in the early 1990s during the war with the Medellín Cartel, and over our study period, rates fell substantially from about 184 per 100,000 inhabitants in 2002 to about 21 (Figure D.1). We note, however, that this range is not only representative of many cities in Latin America, but also of many current

[10] *Operacion Orion*, followed by the demobilization of paramilitary forces, led to a sharp decline in homicides, as the military clamped down on urban militias (Medina and Tamayo, 2011).

cities in the US. For example, in 2019, St. Louis experienced a homicide rate of 64.54, Baltimore a rate of 58.27, and Detroit a rate of 41.45 per 100,000 inhabitants (F.B.I, 2020).

Between 2005-13, 12% of all males (across all age groups) were at some point arrested. Younger individuals are more likely to be engaged in drug trafficking and consumption, whereas slightly older individuals are involved in violent crimes (homicides, extortion, and kidnapping), and the oldest still are involved in property crime. These numbers are high, but are representative of cities across Latin America. Indeed, even the US has an incarceration rate more than six times the typical OECD nation, where one in ten young men from a low-income family may join a gang, 60% of crimes are committed by offenders under the age of 30, and 72% by males (Kearney et al., 2014). Accordingly, arrests in our context are similar to high-crime regions in many parts of the world, and especially Latin America (Dell et al., 2019).

Anthropological studies and in-person interviews show that economic incentives (such as the focus of our study) drive young men in Medellín to join organized crime (Baird, 2011). As many respondents highlight, the reason to join crime is mostly "economic" or for a profitable career.[11] Gangs also actively recruit idle youth that are *amurrao* (local slang, literally: 'sitting on the wall') and without a high-paying job.[12]

Blattman et al. (2018) document Medellín's criminal world as hundreds of well-defined street gangs (*combos*) controlling local territories and organized into hierarchical relationships. They confirm that gangs are profit-seeking organizations, earning money from protection, and coercive services such as debt collection and drug sales.

Often, however, remunerations for gang members are higher than jobs for those with similar levels of education (Doyle, 2016). New recruits are employed to run guns (*carritos*), before transitioning to extortion and trafficking. Blattman et al. (2018) shows that combo foot soldiers earn well above the minimum wage whereas *combo* leaders' earnings "put them in the top 10% of income earners in the city."[13]

Gang boundaries demarcate territory. Operating on a rival gang's turf can lead to retribution, and eventually, gang wars. Individuals do not have to live on the turf they operate in, even though many likely do. Many individuals live in parts of the city not under any specific gang turf, and only a few live near downtown, where much

[11] See *interview with Gato, p264* and *interview with Armando, p197*.

[12] Sector choice is salient during recruitment: "*those guys would hang out around here and be nice to me and say 'come over here, have a bit of money'*" (*interview with El Mono, p191*). The options reflect an occupational choice: "*are you gonna work [for the gang] or do a normal job?*" (*interview with Notes, p193*). Having a 'normal job' means that one is not "hanging around the neighborhood" when the gangs are recruiting. Indeed, those with other jobs pay extortion fees to gangs (*interview with El Peludo, p184*).

[13] During the demobilization of militias in the mid-2000s, many were encouraged to join the formal sector, given identity cards and medical cards (Rozema, 2018).

crime occurs. Multiple gangs operated downtown (and adjacent business districts), which is also a focal point for the transit network. Crime in business districts is not 'local', and so there is a concern that transit networks may increase criminal activity near businesses. These crimes include drug crimes, extortion, and property crime.

In our framework, the transit network may change whether or not individuals work for a gang, and where (which turf). Once they are on the territory, they may engage in various types of (correlated) criminal activity, such as drug production, extortion, and even property crime.

4 The Reduced-form Effects of Transit Lines on Crime

Let us consider the effects of an expansion in the transportation infrastructure on crime. Building a new cable line may either raise or reduce crime in newly connected neighborhoods. For instance, building a new cable may increase criminal activity, by lowering the costs of transit for criminals to newly connected destinations. It may also increase access to legitimate employment opportunities, which in turn, may reduce the relative benefit to criminal activities.

4.1 Impacts on Neighborhoods that Receive a New Station

We begin our analysis with an event study specification that leverages the timing of the rollout of the transit lines across neighborhoods. Our analysis is comprehensive in that we look at seven primary outcomes, leverage all changes to transit times (given available data), and examine heterogeneity by neighborhood characteristics prior to transportation infrastructure expansions.

A standard event study framework would implement the following specifications, first at the neighborhood origin o by year t level:

$$Log\ y_{ot} = \alpha_o + \alpha_t^{(o)} + \sum_{\underline{T} \leq k \leq \overline{T}} \beta_k^{(o)} Station_{o,t-k} + u_{ot}, \tag{1}$$

These capture the behavior of residents in a neighborhood. We also study activities performed at destinations d (regardless of the location of origin residence):

$$Log\ y_{dt} = \alpha_d + \alpha_t^{(d)} + \sum_{\underline{T} \leq k \leq \overline{T}} \beta_k^{(d)} Station_{d,t-k} + u_{dt}, \tag{2}$$

where the subscripts indicate origin o and destination d. We include year fixed effects for the origin-year $\alpha_t^{(o)}$ and destination-year $\alpha_t^{(d)}$ regressions, and neighborhood fixed effects (α_o or α_d). Our main treatment variable is an indicator for whether or not the neighborhood (origin or destination) is within 1 km of a new transit station (Cable K, Cable J, BRT, or Tram).[14] Control neighborhoods are those lying between 1 km and 2 km from the new station. Neighborhoods more than 2 km from the new station are not included in the estimation sample.[15] Neighborhood fixed effects account for all time-invariant characteristics of the neighborhood (historical gang presence, elevation, baseline industrial structure, etc.), while time fixed effects account for any city-level changes over time (new mayor or police chief, city budget on crime or transit, etc.).

Recent advancements in two-way fixed effects methods identify issues regarding negative weights when there is staggered adoption (Borusyak and Hull, 2023; Callaway and Sant'Anna, 2021; de Chaisemartin and D'Haultfœuille, 2020; Sun and Abraham, 2021). We implement our specification using techniques developed by Callaway and Sant'Anna (2021), but show robustness to other methods as well (Figure D.3).

We focus on seven primary outcomes (in logs): number of crimes committed by residents of a neighborhood ('Crime at origin'), number of crimes committed in a neighborhood location ('Crime at destination'), legitimate-sector employment of residents of a neighborhood ('Employment at origin'), legitimate-sector employment in a neighborhood location ('Employment at destination'), legitimate-sector earnings for residents ('wages at origin'), legitimate-sector earnings at the workplace ('wages at destination'), and residential rental rates for housing ('Rents').

Figure 4 shows, first, that we do not detect meaningful differential pre-trends in our seven outcomes between neighborhoods more and less proximate to new stations, supporting a causal interpretation. Second, most impacts are gradual and grow over time, perhaps reflecting that many decisions on whether to participate in criminal or legitimate enterprises, and in which neighborhood, takes time.

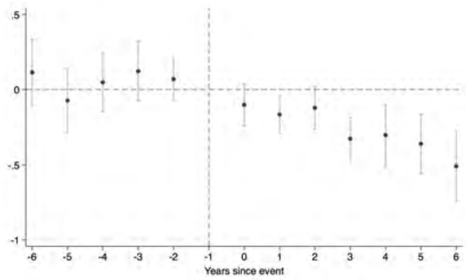
Next, when looking at crimes committed by the residents of a neighborhood, we see a gradual decrease in such crimes. That is, receiving more transit access near one's residence, reduces criminal participation. Yet, as a destination of criminal activity, there is no meaningful change, with perhaps a slight decrease many years later. Transit lines can have countervailing effects on the destinations of crimes: bringing crime to certain types of neighborhoods, even as overall crime rates may fall. Below, we show that this average (non)effect on crime destinations hides meaningful heterogeneity.

[14] The 2021 northwest cable is not included, given the lack of post-period data.

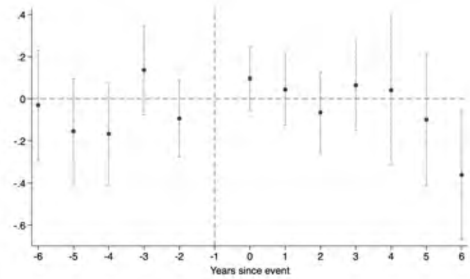
[15] This choice is consistent with evidence on spatial diffusion presented in Section 4.2 below. A 1–2 km neighborhood contributes to the control pool up to, but not after, the year it receives its own station.

Figure 4: Event Studies: Effects of new transit lines

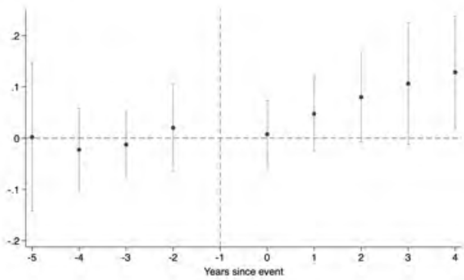
(a) Log Crime at origin



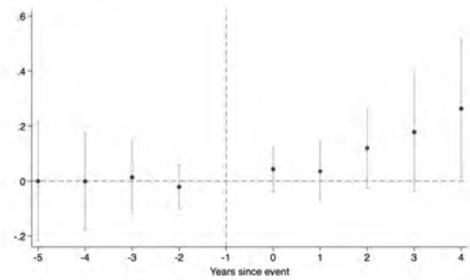
(b) Log Crime at destination



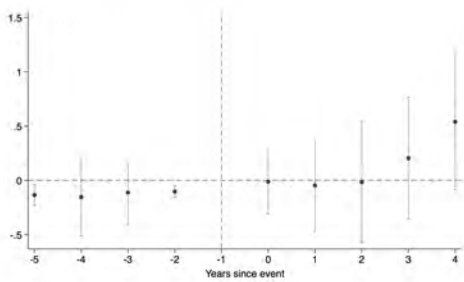
(c) Log Employment at origin



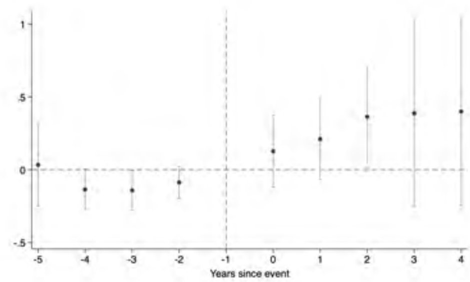
(d) Log Employment at destination



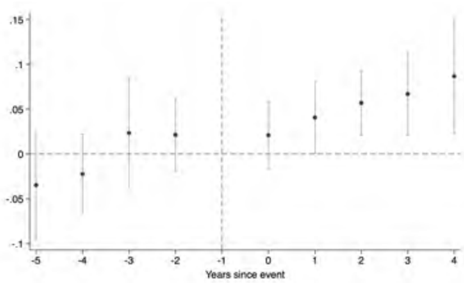
(e) Log Wages at origin



(f) Log Wages at destination



(g) Log Rents



Notes: Figure shows the effect of a new transport building on crime, employment, rents, and wage outcomes, using Callaway and Sant'Anna (2021). We use as new transport buildings: Cable K started operations in 2004, Cable J started operations in 2008, Rapid Bus Transport started operations in 2012, and Tram started operations in 2015. The crime database at origin and destination goes from 2002 to 2015. The employment at origin is from 2004 to 2016, and rent data from 2005 to 2018. The employment at destination and wages database goes from 2007 to 2017. The corresponding specifications are Equations 1 and 2.

In contrast, for both origins and destinations of legitimate-sector employment, receiving a transit station increases employment. Though less precisely estimated, earnings effects patterns are consistent with legitimate-sector employment effects. The imprecision suggests potential heterogeneity that we explore further below. Finally, residential rents increase in areas closer to new transit stations.

We summarize these results in Table 1. The table reports estimates from methods developed by Callaway and Sant'Anna (2021), and all definitions are consistent with the event study specification. The top panel shows our baseline specification, which only includes neighborhood and year fixed effects. Panel B introduces baseline (pre-2004) controls (interacted with year indicators), including population, earnings, share of formal workers, and school-goers. Panel C includes comuna-by-year fixed effects.

The results mirror our event study estimates. When receiving a new station, the residents of a neighborhood switch the enterprises they are engaged with on average over the post-treatment window: crime at the origin level falls by 21-26%, while employment increases by 9-13%. Rental rates in these neighborhoods also increase by roughly 5%. In terms of destinations, in areas around new stations, there is more legitimate sector work and higher earnings generated on net, and some evidence of a possible (insignificant) net reduction in crime.

Robustness to alternative TWFE methods and outcomes in levels: We explore the robustness of these main results in the Appendix. First, in Figure D.3 we show robustness using two-way fixed effects methods suggested by Sun and Abraham (2021) and Borusyak et al. (2024). Our results are similar to before, with a slightly stronger fall in crime destinations. Figure D.4 re-examines the event study for non-monetary variables using levels instead of logs, and shows similar patterns.

Robustness to transit infrastructure expansion type and types of crime: Figure D.5 shows heterogeneity in impacts by type of transit infrastructure and type of crime. The openings of cable lines have more meaningful impacts on criminal participation, compared to the non-cable transit. All types of crime categories see reductions, but the impacts on property crime are less precisely estimated.

Robustness to dropping BRT: In Table D.1, we do a more involved exploration of the identifying variation. First, we drop variation generated by the BRT for a few reasons. The BRT was expanded in various waves, making the timings and intensity of expansion potentially diffused. It traversed the middle of the city (along the pre-existing metro lines), and the plan documents make it difficult to identify what the underlying determinants of the station locations were. In contrast, planning documents clearly documented what determined cable lines, allowing us to explore an instrumental variables strategy that leverages such variation below. Accordingly, as we might expect, Panel A of Table D.1 shows our main specification, without the BRT, and finds impacts that are stronger and more precisely estimated.

Table 1: The Impacts of a New Transit Station on Economic Outcomes

	Log Crime Origin	Log Crime Destination	Log Emp Origin	Log Emp Destination	Log Wage Origin	Log Wage Destination	Log Rent
	Panel A: Baseline specification						
Post × Station	-0.244***	-0.126	0.090**	0.230***	0.144	0.291	0.050**
	(0.042)	(0.128)	(0.040)	(0.060)	(0.239)	(0.196)	(0.017)
	Panel B: Including pre-2004 controls						
Post × Station	-0.213***	-0.118	0.121**	0.263***	0.134	0.344*	0.048**
	(0.056)	(0.091)	(0.044)	(0.056)	(0.239)	(0.199)	(0.018)
	Panel C: Including Comuna-by-Year Fixed Effects						
Post × Station	-0.264***	-0.122	0.131***	0.284***	0.208	0.273	0.049**
	(0.058)	(0.088)	(0.040)	(0.060)	(0.239)	(0.196)	(0.017)
Observations	2,548	2,324	2,215	2,093	2,215	2,093	2,730
Mean Dep Var (levels)	33.094	119.462	3,249.84	5653.971	0.962	0.879	0.431
Years data	2002-2015	2002-2015	2004-2016	2007-2017	2004-2016	2007-2017	2005-2018

Note: Table shows the effect of a new transport building on crime, employment, rents, and wage outcomes, using Callaway and Sant'Anna (2021). We use as new transport buildings: Cable K started operations in 2004, Cable J started operations in 2008, Rapid Bus Transport started operations in 2012, and Tram started operations in 2015. The crime database at origin and destination spans 2002 to 2015. The employment at origin is from 2004 to 2016, and rent data from 2005 to 2018. The employment at destination and wages database goes from 2007 to 2017. Mean of dependent variables are reported in levels. Wages are measured in millions of pesos. All specifications include year and neighborhood fixed effects and standard errors clustered at the neighborhood level.

Robustness to dropping first and last station neighborhoods: The goal of the cable infrastructure was to connect the outskirts of the city to the main (pre-existing) metro line. Yet, we may be concerned that these peripheral neighborhoods were chosen for a particular purpose that may confound our estimates (beyond what is captured by the various fixed effects or reflected in tests of pre-trends). In Panel B of Table D.1, we conduct an exercise where we start with all non-BRT stations (as in Panel A) but then drop the neighborhood within 2kms of the first and last stations on each line, and instead just conduct our exercise based on the incidentally treated neighborhoods that happened to be on the path between them. Since cables are mostly straight lines, being on the route is somewhat exogenous, conditional on the nodes. Our results are robust to this specification.

Robustness to using IV: Finally, for a cable to be built, the slope of the mountain between the start and end points must be sufficiently steep. For example, slope was a key consideration in figuring out where to connect a cable from northeastern Medellín to the main line.[16] We leverage this variation in an instrumental variables strategy.[17] We first determine a set of possible lines that could have been built by connecting each peripheral neighborhood to the closest arterial metro station. We then calculate the slope of the mountain along each of those lines. We define the slope of each possible line to be the difference in altitude between the start and end points divided by the length of the line. Empirically, we find that (as suggested by the engineering documents) lines built have higher slopes than those not built. Table D.2 shows the first stage results predicting when a new line will be built as a function of the slope below, with an F-stat of at least 63. Panel C of Table D.1 shows the two-staged least squares (2SLS) results of this instrumental variables estimation, with qualitatively similar impacts to our baseline specification in Panel A.

4.2 Heterogeneity by Neighborhood Economic Structure

While this reduced-form analysis is informative of what happens on net in places near new transit centers for the particular instances we study, the net outcomes clearly depend on complex underlying relationships. To generalize these results to broader policies or interventions that may change commute times to differing degrees and/or for a different set of neighborhoods, we must investigate the confluence of market forces that determine the responses for specific individuals and neighborhoods.

The fall in crime as a result of the cable expansion, on average, perhaps reflects that being connected allows youth access to legitimate employment opportunities in other parts of the city, lowering the attractiveness of criminal involvement. This may be likely if, for instance, criminal activity is more localized than legitimate-sector employment. If most crime centers around local street gangs, then not being able to easily go to other parts of the city may mean that, in neighborhoods that have street gangs, youth will be drawn into crime. If so, to engage in crime, individuals in such neigh-

[16] Quote from: Trujillo, Camilo (2015) "El Metro contempla construir la línea K 2 hacia Santo Domingo". El Colombiano newspaper (translated):

> *As debated later in year 2015, having steep mountains was among the requirements for implementing cable lines rather than other transport solutions, as it became evident when the ETMVA dismissed the possibility of building a cable line departing from El Tricentenario station to "El Pichano" to cover the northwestern area of the city, given the low slope of that hillside.*

[17] We may also expect the timing of when lines are built and become operational to be generally exogenous. For example, plans for the North-South metro line were drawn up in the 1980s, but the line itself was not inaugurated until 1995. *Sources: Department of National Planning (1982a)"Projecto Tren Metropolitano De Medellín Conpes Policy Document No. 1886.*

borhoods stay in their neighborhoods, but to participate in the legitimate sector, they must travel far by paying a high travel cost. Once these street gang neighborhoods are connected to the cable line, crime may fall, as youth from these neighborhoods can easily access legitimate activity in other parts of the city.

However, such a narrative would imply that if the economic structure of the neighborhood were different, then being connected may have had the opposite effect. Suppose, for instance, a neighborhood with no street gangs was suddenly added to the transit network, opening up access to other parts of the city, including other gang neighborhoods. Then, we may have an increase in legitimate activity as more individuals come and access these legitimate-sector jobs. But we may also have youth from these newly connected neighborhoods joining criminal enterprises in other neighborhoods to which they now have easy access.

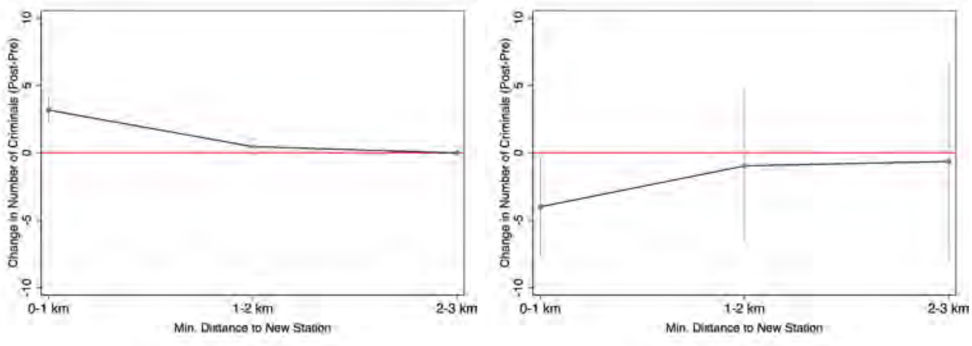
Theoretically, this suggests that what we saw in Section 4.1 may depend on the underlying economic structure of the neighborhoods which are newly connected.For example, it is ambiguous whether high baseline crime areas should see an increase or decrease in criminal activity. On the one hand, individuals operating in such areas may choose to work downtown in the legitimate sector after getting access to the transit network. On the other hand, these may be regions where the returns to criminal activity are high, and so may attract more criminal activity when connected.

To examine this, we consider a critical aspect of heterogeneity that directly relates to our analysis: the role played by access to different types of criminal opportunities. We examine this heterogeneity, by distance bins, allowing us to simultaneously test for the presence of spatial spillovers. The effects we document in the event studies capture relative changes: the impacts on neighborhoods near a station, relative to neighborhoods farther away. Yet, if there is a shift in economic activity to neighborhoods farther away, the aggregate impacts on criminal activity may be unclear. Examining how the effects vary across distance bins sheds light on geographic spillovers.

To examine these neighborhood patterns, we combine all new stations and consider the change (post minus pre) in crime rates. To be transparent, we show the effects along various distance bins to non-parametrically describe these relationships. Figure 5 shows meaningful heterogeneity in criminal activity originating from neighborhoods near the stations (0-1km). The reduction in criminal participation is confined to neighborhoods that have high baseline levels of crime (right panel). The left panel suggests a smaller offsetting increase in crime participation in areas that had low levels of baseline criminal activity. Note, we do not observe meaningful geographic spillovers in criminal activity to areas 1-2kms away (our comparison group in the event study), nor

Figure 5: Changes in Crime at the Origin by Baseline Crime, and Distance (in km) Bins

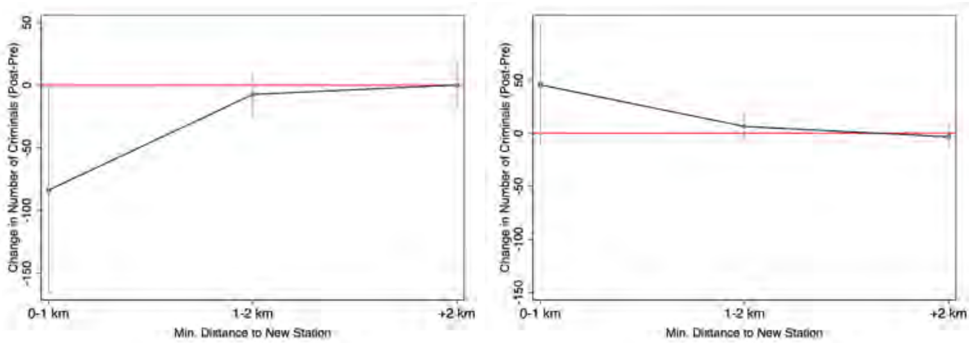
(a) Low Baseline Crime Areas (b) High Baseline Crime Areas



Notes: Figures plot the change in crime over time as a function of the distance to the nearest station. The vertical axes plot the arrest rate in the post-station period minus the arrest rate (arrests per year) in the pre-period. The horizontal axes show distance bins. The left panel restricts the sample to neighborhoods that have below median baseline crime rates, whereas the right panel is for above median baseline crime rates.

Figure 6: Changes in Crime Destinations by Baseline Income, and Distance Bins

(a) Low Income Areas (b) High Income Areas



Notes: Figures plot the change in crime over time as a function of the distance to the nearest station. The vertical axes plot the arrest rate in the post-station period minus the arrest rate (arrests per year) in the pre-period. The horizontal axes show distance bins. The left panel restricts the sample to neighborhoods that are below first tercile baseline income, whereas the right panel is for above third tercile baseline income.

at 2-3kms away. Yet, as we argue with the help of our model below, there may be spatial redistribution across the transit network to other parts of the city.

Figure 6 shows crime destinations by baseline income of neighborhood residents. Again, we see substantial heterogeneity in impacts, with the reduction in crime concentrated in areas with low baseline incomes. There is some evidence that criminal activity may have risen in high-income areas near stations, but the estimate is insignificant, and the absolute magnitude is much smaller than the reductions seen in low-income areas. The heterogeneity in criminal responses is indicative of how the spatial distribution of economic opportunities is important in determining the local change in crime as a result of changes in access to different neighborhoods. Together, these results show meaningful heterogeneity in how criminal activity responds, by baseline access to criminal and economic opportunity (and by distance from the new stations).

4.3 Panel Gravity Equations and Neighborhood-by-Time Shocks

Above we describe the effects of being near a newly built station, and not the consequences of changes in travel time between neighborhoods. Indeed, that is what we will show below in our model to be the important determinant of changes to the spatial structure of criminal and legitimate activity, and the overall changes to crime levels in the city. The difference-in-differences analysis, so far, only tells us that crime is reduced in treated *relative* to control neighborhoods. As neighborhoods are connected, these results may indeed also reflect increases in criminal activity in neighborhoods farther away from stations. For instance, if living near a station means a criminal can travel farther away to new neighborhoods, then crime may increase in such neighborhoods farther away, even as it reduces in neighborhoods near the newly connected station.

The nature of such general equilibrium consequences necessitates a spatial general equilibrium model to make meaningful statements about what happens to crime and legitimate activity in aggregate. Yet, to identify important parameters of the model, we leverage the rollout of the cable in a manner that is no longer confounded by other differences across neighborhoods and time. Accordingly, we now move towards the standard panel gravity equation setup, where we wish to know how changing the travel time between an origin o and destination d affects the flow of criminals from the origin to destination neighborhoods. If the transit elasticity for criminals θ_c is higher than for legitimate employment, then crime is more sensitive to travel time, and (conditional on sector choice) there may be a greater dispersion in criminal activity as a result of changes to travel time.

To execute this analysis, we use information on how travel times between any origin and destination pair change as and when new cables are introduced. This variable $Travel\ Time_{odt}$ varies at the origin-destination-time level, allowing us to further account for other confounding variables, and strengthen identification.

While the specifications so far control for a large dimension of fixed effects that account for differences across neighborhood pairs or time, one may be concerned that there are concurrent changes at the neighborhood-by-time level that confound our estimates. For instance, gang wars that happen to coincidentally break out in neighborhoods close to newly built stations (for reasons unrelated to the station's presence) would bias our estimates. Similarly, changes in policing structure in the neighborhoods over time, in a way that somehow correlates with distance to the station, would be a potential confounder. These changes in gang wars and policing may occur differentially over time at either the origins or destinations of criminal activity.

Locations of stations and metro lines may also be chosen in a way that reflect other changes in place-based policies, or trends in neighborhood characteristics. As such, it is important to control for neighborhood-by-time fixed effects. Finally, neighborhood pairs (origins-by-destinations) may differ on a host of other characteristics, such as distance, industrial similarity, and gang affinity, that may confound estimates.

Fortunately, the richness of our data allows us to control for all such effects, by including origin-by-time fixed effects γ_{ot}, destination-by-time fixed effects γ_{dt}, and origin-by-destination comuna fixed effects γ_{od}:

$$Crimes_{odt} = exp\left(\gamma_{ot} + \gamma_{dt} + \gamma_{od} + \beta\, Travel\ Time_{odt}\right) \epsilon_{odt} \tag{3}$$

We return to Equation 3 later in our analysis as it helps causally identify the crucial parameters of our model. Given the presence of zero flows, we estimate it using Poisson pseudo maximum likelihood (PPML). Here, γ_{ot} and γ_{dt} account for neighborhood-by-time level shocks, such as gang wars, local economy changes, or changes in policing over time by neighborhood, and γ_{od} control for origin-destination comuna-level time-invariant features (Tsivanidis, 2023). As such, the only remaining threat to identification would be if there were time-varying shocks to origin-destination pairs that were unaccounted for by the fixed effects. We show later that β is structurally informative of crucial economic elasticities that drive the spatial distribution of crime and legitimate activity across the city. We also estimate the same specification for formal-work flows.

In Table 2, we estimate Equation 3. Reductions in the travel time between origins o and destinations d raise the amount of criminal activity that flows from o to d. The corresponding semi-elasticities with respect to travel time are -0.0676 for all crimes, and -0.0644 for violent crimes. Yet, as we show in the model, what is equally important is the change in flows of legitimate employment as a result of new cables. If legitimate employment is less responsive, then new lines are less likely to greatly affect the flow of legitimate-sector workers. Yet, improved access to legitimate-sector jobs may

Table 2: The Effects of Travel Time From Origins to Destinations

Travel Time From Origin To Destination	Any Crime	Violent Crime	Legitimate Work
Minutes From Origin to Destination	-0.0676***	-0.0644***	-0.0386***
	(0.0034)	(0.0064)	(0.0078)
Observations	1,013,054	1,013,054	217,083
Data Structure		Origin-Dest-Time	
Destination-by-Time FEs	Yes	Yes	Yes
Origin-by-Time FEs	Yes	Yes	Yes
Destination-by-Origin FE	Yes	Yes	Yes
SE Cluster		2-way Destination and Origin	

Notes: Tables show the effect of changes in travel time between origin-destination pairs on the resulting flows in crime and legitimate-sector workers between these neighborhoods. We estimate this standard gravity equation using Poisson pseudo maximum likelihood (PPML) with high-dimensional fixed effects, and two-way cluster our errors at the origin and destination level.

lower overall criminality by way of sector choice. In the last column of Table 2, we replace the outcome to be legitimate-sector work, and find that the travel-time elasticity of legitimate-sector flows is lower than that of crime, at about -0.0386. We return to Table 2 below and discuss how these estimates inform our model's parameters.

4.3.1 Robustness

One may also expect that gang boundaries affect the commuting elasticity. We estimate this gravity equation again, interacting the commuting time with indicators for whether the commute crosses gang boundaries. Table D.3 shows that in Medellín, gang boundaries do not seem to substantially affect the commuting elasticity for either crime or legitimate sector work. Though at first surprising, this empirical reality likely reflects both that overhead cables allow commuters to skip over neighborhoods entirely without violating any gang boundaries, and, maybe also that individuals need not reside in the territory they work in (especially as many crimes occur downtown).

One may also consider the possibility, that these elasticities vary by type of crime. We classify crimes into various categories, and also build on previous work (Khanna et al., 2023) to define crimes that are likely to be associated with criminal enterprises (LACE).[18] We also identify crimes that are less likely to be associated with longer com-

[18] For a subset of arrests, we know whether or not the arrested individual was associated with a gang, cartel, or urban militia. We train our data on this sub-sample to classify all crimes as LACE or non-LACE. For a list, see Khanna et al. (2023).

mutes: we use baseline data (pre 2004), and identify 'local crimes' as those with the lowest (below percentile 25) average commute time between origin and destination. 'Domestic crimes' (like domestic violence) is the largest category of local crimes. Table D.4 shows that for non-local crimes, the elasticities are similar in magnitude across different types of crime, especially as most of these crimes are likely to be associated with criminal enterprises (LACE). On the other hand, there does not seem to be any meaningful impact on local crimes and domestic crimes.

Next, we examine these gravity-style relationships in an event study. Here, we see how commuting flows between an origin and destination respond to changes in commute times. We present the results below in Figure D.6. It shows that when two neighborhoods are connected, it increases both the flow of criminals and of legitimate sector workers. Finally, in Figure D.7 we test our functional form assumptions by plotting a (residualized) semi-parametric relationship between crime flows and travel time. Across the various types of crime, we find a meaningful log-linear relationship between criminal flows and travel time.

4.4 Individual-Level Sorting and Occupation Choice

Our neighborhood-level regressions document a decrease in criminal participation when the residents of a neighborhood are proximate to a newly built transit station. Now, we explore this relationship further by examining whether individuals are changing what enterprises they participate in, or whether this is driven by a shift in who lives in these neighborhoods.

We leverage the full extent of our unique individual-level data to construct a panel of individuals. We use the Sisben waves to identify who moves neighborhoods, and who stays. As our structural framework will model both the neighborhood choice and occupational choice, we first aim to determine how important each of these choices are in driving the aggregate reduction in crime. We estimate the following individual-level regression, with individual i and year t fixed effects:

$$Crime_{it} = \alpha_i + \alpha_t + \beta \left(Station_{i(o)} \times Post_t \right) + \epsilon_{it} \tag{4}$$

Our outcome of interest, is if individual i was ever arrested for a crime, in period t. We estimate these regressions for various sub-samples: (1) the full sample, (2) all movers in or out, (3) those who move into the neighborhood, (4) those who move out, and (5) those who never move. These various subsamples help us unpack, for example, whether the changes in crime are driven by those who (3) move into the neighborhood, or (5) those who always stay in that neighborhood. We conduct this analysis for two different relevant slices of the data: first, using those individuals who consistently lived in treated (within 1km) or control (1 to 2km) distances from a station (Table 3); and, second, using those individuals who *ever* lived in a treated or control neighborhood (in Appendix Table D.5).

Table 3 shows that for all individuals, there was a reduction of 4.4% in criminal activity. This effect was almost entirely driven by crime reductions for those who stay in the neighborhood (a 5% reduction), and do not move neighborhoods. The results are similar using the *ever lived in* neighborhood resident definition (Table D.5).

Table 3: Individual-Level Regressions: Neighborhood Sorting vs Occupational Choice

	Crime (1/0)				
	All	Movers	Mover In	Mover Out	Stayers
Post $\times$ Station	-0.0004***	-0.0002	0.0006	-0.0002	-0.0006***
	(0.00015)	(0.0002)	(0.0006)	(0.0010)	(0.0002)
Observations	6,342,262	1,821,606	303,053	252,239	4,520,656
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean	0.0101	0.0054	0.0062	0.0056	0.0121
Mean Control	0.0099	0.0048	0.0066	0.0055	0.0120

Notes: The table shows the Diff-in-Diff estimation of the effect of transit lines on the probability of arrest at the individual level. The sample consists of individuals living in treated or control neighborhoods from 2002 to 2015. Table D.5 shows results for a sample that *ever* lived in these neighborhoods. 'Mover In' and 'Mover out' are individuals who move into or out of treated neighborhoods. Neighborhoods around 1 km from a new transport building are treated. Neighborhoods between 1km and 2 km from a new transport building are controls.

Summary. Taken together, our empirical reduced-form relationships document that criminal participation among residents falls in neighborhoods close to a new station, relative to those farther away. This corresponds to increases in legitimate sector employment, wages, and property prices for residents of these neighborhoods. Furthermore, there is an increase in legitimate sector work and wages in workplaces situated near newly built stations (again, relative to places farther away).

Yet, there is marked heterogeneity in these effects by baseline neighborhood characteristics. Much of these effects are driven by individuals choosing different occupations, rather than moving neighborhoods. One may be concerned that this neighborhood-time level variation may be confounded by neighborhood-specific shocks (policing, gang wars, etc.). Accordingly, we lean on gravity regressions, conditioning on high-dimensional fixed effects for origin and destination by time unobservables and origin-destination pair time invariant unobservables, to confirm increased commuting flows between newly linked neighborhoods. Yet, determining how these changes in commuting flows and occupations translate into aggregate city-level impacts on crime rates in the presence of meaningful heterogeneity and spillovers requires a model.

Understanding how urban transit impacts criminal participation across neighborhoods and, in turn, how such participation affects welfare and related outcomes within a city is challenging for several reasons. First, recent studies of crime have emphasized that criminal activity imposes negative externalities on other sectors of the economy (Melnikov et al., 2022; Rozo, 2018), as well as on neighborhood amenities (Gibbons, 2004). Such externalities imply that legitimate economic activity, as well as sorting patterns across locations, respond to criminal activity, and in turn, criminal activity responds to them. Second, the differences in commuting patterns documented above suggest that connecting neighborhoods to urban transportation infrastructure will not only affect newly-connected neighborhoods by changing economic opportunity in that location (Dix-Carneiro et al., 2018; Sviatschi, 2022). Other neighborhoods will also be affected as criminals and workers change their commute patterns across the city.

5 Model

Having established robust reduced-form evidence, we now endeavor to overcome the identification challenges discussed above as well as to study the general equilibrium implications of criminal activity. We outline an urban quantitative model with crime that links the mechanisms of sectoral choice, commuting costs, and cross-sector externalities in a unified equilibrium model. This section concisely introduces the structure, highlighting novel additions to formulations in prior studies, before turning to parameter estimation.

We adapt recent urban spatial models (Ahlfeldt et al., 2015; Heblich et al., 2020), to include crime and cross-sectoral externalities. Individuals choose between crime and legitimate work as a function of firm and commuter market access (Tsivanidis, 2023; Zárate, 2023). We incorporate intersectoral spillovers (Heblich et al., 2021), potentially creating feedback loops, whereby crime generates negative externalities on legitimate employment and neighborhood amenities. (Almagro and Domínguez-Iino, 2022).

We first describe an S-sector framework that generalizes Zárate (2023) by embedding negative externalities from criminal activity on local productivity and amenities. City-level outcomes can be written as functions of commuter and firm market access.

This yields reduced-form regressions linking neighborhood outcomes to structural parameters. Finally, we show that in a two-sector model (crime and legitimate sector), these coefficients are informative of the sign of the externalities.

Framework. Consider a city with discrete neighborhoods indexed by $o, d = 1, ..., N$. There are $s = 1, ..., S$ sectors in the economy. There are $S + 2$ types of agents in the economy: workers, landlords, and owners of sector-specific fixed factors. There is a fixed measure $\bar{L}$ of workers who are endowed with a unit of labor, which is supplied inelastically. Workers have idiosyncratic preferences for residences, workplaces, and sectors, and are geographically mobile within the city.

Firms in each neighborhood sector produce freely tradable varieties consumed within the city and potentially in a foreign destination, $\mathcal{F}$. Firms have a constant returns to scale production function, hire labor, and rent a sector-specific fixed factor.

Workers Sector-Residence-Workplace Decisions. Workers have Cobb-Douglas preferences over a final good (an aggregate of sectoral consumption goods) and housing. The indirect utility of worker x living in o, working in sector s, and commuting to d is:

$$U^s_{od}(x) = \frac{w^s_d (\tau_{od})^{-1}}{P_o^{\beta} Q_o^{(1-\beta)}} \varepsilon^s_{od}(x), \quad 0 < \beta < 1,$$

w^s_d is the sector-s wage in d; τ_{od} the iceberg commute cost; P_o the final consumption price index; Q_o the residential floorspace price. The final price index is Cobb–Douglas in sectoral prices: $P_o = \prod_{s=1}^{S} (P^s_o)^{\xi^s}$, and $\sum_s \xi^s = 1$.

Within sectors, the price indices aggregate neighborhood varieties $P^s_o = \left[\sum_d (p^s_{do})^{1-\sigma^s}\right]^{\frac{1}{1-\sigma^s}}$, $\sigma^s > 1$, where σ^s is the elasticity of substitution between varieties in a sector and p^s_{do} is the price of the neighborhood variety d in sector s sold in o.

Idiosyncratic preferences, $\varepsilon^s_{od}(x)$, follow a multivariate Frechet:

$$H(\overrightarrow{\epsilon}(x)) = \exp\left[-\sum_o \left(\sum_s B^s_o \left(\sum_d (\epsilon^s_{od}(x))^{-\theta^s}\right)^{\frac{\kappa}{\theta^s}}\right)^{\frac{\eta}{\kappa}}\right], \text{ with } \eta < \kappa < \theta^s \quad \forall s,$$

where θ^s captures sector-specific sensitivity to commute costs, κ captures sectoral choice sensitivity to differences in wage indices, and η captures residence-choice sensitivity to differences in residence-specific characteristics.

Residential amenities B_o^s capture reasons that make certain origins attractive for individuals of specific sectors. They are given by $B_o^s = b_o^s \prod_{s'} (L_o^{s'})^{\omega^{s's}}$, where b_o^s is a sectoral amenity fundamental in neighborhood o, and $\omega^{s's}$ captures cross sectoral externalities (positive or negative) induced by workers from sector s' working in neighborhood o, $L_o^{s'}$, on residents from sector s living in neighborhood o.

Frechet properties imply the share living in o, working in s, commuting to d is:

$$\pi_{od}^s = \underbrace{\frac{\left(P_o^{-\beta} Q_o^{-(1-\beta)} W_o\right)^\eta}{\sum_{o'} \left(P_{o'}^{-\beta} Q_{o'}^{-(1-\beta)} W_{o'}\right)^\eta}}_{\pi_o} \underbrace{\frac{B_o^s \left(W_o^s\right)^\kappa}{\sum_{s'} B_o^{s'} \left(W_o^{s'}\right)^\kappa}}_{\pi_{o|o}^s} \underbrace{\frac{\left(w_d^s\right)^{\theta^s} \left(\tau_{od}\right)^{-\theta^s}}{\sum_{d'} \left(w_{d'}^s\right)^{\theta^s} \left(\tau_{od'}\right)^{-\theta^s}}}_{\pi_{od|os}^s}, \tag{5}$$

where:

$$W_o \equiv \left[\sum_{s'} B_o^{s'} \left(W_o^{s'}\right)^\kappa\right]^{\frac{1}{\kappa}} \tag{6}$$

$$W_o^s \equiv \left[\sum_{d'} \left(w_{d'}^s\right)^{\theta^s} \left(\tau_{od'}\right)^{-\theta^s}\right]^{\frac{1}{\theta^s}} \tag{7}$$

are origin-specific, and origin-sector specific wage indices, respectively. Worker expected utility is:

$$\bar{U} = \gamma \left(\sum_o \left[P_o^{-\beta} Q_o^{-(1-\beta)} W_o\right]^\eta\right)^{1/\eta}. \tag{8}$$

Production. Firms in sector s, neighborhood d, use labor L_d^s and a sector-specific factor F_d^s with constant-returns Cobb–Douglas production:

$$y_d^s = A_d^s \left(L_d^s\right)^{\alpha^s} \left(F_d^s\right)^{1-\alpha^s}.$$

They pay wage w_d^s and rent the factor at q_d^s. With constant returns to scale and perfect competition, prices equal unit costs:

$$p_d^s = \left(\alpha^s\right)^{-\alpha^s} \left(1-\alpha^s\right)^{-(1-\alpha^s)} \frac{\left(w_d^s\right)^{\alpha^s} \left(q_d^s\right)^{(1-\alpha^s)}}{A_d^s}.$$

Productivity is given by $A_d^s = a_d^s \prod_{s'} (L_d^{s'})^{\lambda^{s's}}$, where a_d^s are fundamentals and $\lambda^{s's}$ captures cross-sector externalities (positive or negative) induced by workers from sector

s' on firms from sector s location d.[19] Destination-sector specific varieties are freely tradable across neighborhoods, so $p^s_{do} = p^s_d$ for all o.

This formulation captures that individuals choose between working for a legitimate or criminal enterprise—an explicit recognition that most illegal activity in this setting occurs through organized firms rather than atomistic agents.

Workers and Residents by Market Access. Let L^s_d denote sector-s workers commuting to d, and R^s_o sector-s residing in o. From commute choice probabilities, commuter market clearing by sector implies:

$$L^s_d = \sum_o \pi^s_{od|os} R^s_o. \tag{9}$$

The denominator of the conditional commute choice probabilities in Equation 5 reflects access to sector-s jobs for residents of o, or sector-specific commuter market access (CMA^s_o). Similarly, sectoral Firm Market Access (FMA^s_d) summarizes sector-s firms' access to workers in d. Appendix B.1 shows these terms are related through the following equations that depend on commute costs, workers in each destination and sector, and residents in each origin and sector:

$$\text{CMA}^s_o = \sum_d \frac{\tau_{od}^{-\theta^s}}{\text{FMA}^s_d} L^s_d \quad \text{and} \quad \text{FMA}^s_d = \sum_o \frac{\tau_{od}^{-\theta^s}}{\text{CMA}^s_o} R^s_o \quad , \tag{10}$$

which can be solved up to scale, given commute costs, sectoral labor/resident counts, and commute elasticities.

Market Clearing. Average income per worker in o, is the sum of the sector-destination wages weighted by commute shares: $v_o = \sum_s \sum_d \pi^s_{o|s} \pi^s_{od|os} w^s_d$. Total neighborhood income is the sum of income of workers and specific factors: $I_o \equiv v_o R_o + \sum_s q^s_o \overline{F}^s_o + Q_o \overline{H}_o$, where $\{\overline{F}^s_o\}^S_{s=1}, \overline{H}_o$ denote the total amount of the fixed factor of sector s and of residential housing in origin o, respectively. Goods and housing market clearing of each destination-sector-specific variety is:

$$p^s_d y^s_d = \xi^s (p^s_d)^{1-\sigma^s} \sum_{o \in \{\mathcal{M}, \mathcal{F}\}} \left(\frac{I_o}{(P^s_o)^{1-\sigma^s}} \right) \quad \text{and} \quad Q_o \overline{H}_o = (1-\beta) I_o$$

[19] While our baseline specification adopts the standard log-linear form for externalities (Ahlfeldt et al., 2015; Tsivanidis, 2023), Appendix B.3 shows that, under some conditions, Market Access regressions can identify the sign of cross sectoral productivity externalities in a non-parametric manner.

where $\mathcal{M} = \{1, ..., N\}$ represents all neighborhoods in the city and $\mathcal{F}$ is a representative foreign market. Labor market clearing implies that sectoral labor demand equals labor supply, and perfect competition implies zero profits.

City Outcomes as a Function of Firm and Commuter Market Access. Appendix B.3.1 shows changes in our key outcomes can be expressed as a function of changes in commuter and firm market access.[20]

$$d \log \boldsymbol{g_j} = \sum_{s \in \mathcal{S}} \boldsymbol{\beta}^s_{jR} d \log CMA^s_j + \sum_{s \in \mathcal{S}} \boldsymbol{\beta}^s_{jF} d \log FMA^s_j + d \log \boldsymbol{e}^s_j, \tag{11}$$

where $\boldsymbol{g_j}$ is a vector of neighborhood j outcomes, and $\mathcal{S}$ is the set of market sectors.

These reduced form coefficients depend on structural parameters. The cross-sectoral externalities influence the sign of these coefficients.[21]

Two Sectors Application: Legitimate Sector and Criminal Sector

We now go from the general set-up to a two-sector framework: legitimate (ℓ) and criminal (c), $s \in \mathcal{S} = \{\ell, c\}$. In the baseline model, local consumption of criminal goods is zero ($\xi^c = 0$), and transport investments do not affect global prices or international demand for criminal goods.[22] The legitimate good is perfectly substitutable and freely tradable across neighborhoods; its price is normalized to one. Regarding externalities, we allow for cross-sector externalities from the criminal sector on legitimate productivity and amenities, as well as within-legitimate sector agglomeration externalities in productivity and amenities.[23]

Appendix B.3 derives changes in key outcomes, including residents by sector, legitimate wages, and rents, as functions of changes in sectoral commuter and firm market access. It shows that coefficient signs depend on cross-sector externalities.

[20] Appendix B.3.1 discusses how expressing these outcomes as log linear functions of commuter and firm market access requires approximations close to infinite transport costs. Our full model solutions do not rely on the approximations.

[21] The reduced form coefficients are indexed by j because these coefficients depend on baseline characteristics of each neighborhood, such as the share of workers participating in each sector.

[22] We assume no neighborhood is large enough to affect the global price of criminal goods. This is justified since almost all of coca output in Colombia is destined for foreign markets: in 2009, only about 1.2% of Andean production was consumed locally, with the vast majority exported to Europe and North America (United Nations Office on Drugs and Crime (UNODC), 2011).

[23] Specifically, $A^\ell_d = a^\ell_d \left(L^\ell_d\right)^\zeta \left(L^c_d\right)^\lambda$, and $B^\ell_d = b^\ell_d \left(L^\ell_d\right)^\psi \left(L^c_d\right)^\omega$. Appendix C.3 extends the model to a more general externality specification and shows results are robust to such extension.

Market Access Regressions. The system of equations 11 links structural parameters to reduced-form regressions of outcomes on commuter and firm market access. Appendix B.3.1 derives the mapping between reduced-form coefficients $\boldsymbol{b}_F^c, \boldsymbol{b}_F^\ell, \boldsymbol{b}_C^c, \boldsymbol{b}_C^\ell$ and model parameters. Table 4 reports estimates using crime, legitimate labor, wages, and rents at origin and destination. Because outcomes and market access are equilibrium objects shaped by the transport network, we apply Borusyak and Hull (2023) to control for expected market access, and instrument market access with predicted access based only on transport times. Table 4 presents specifications with expected access controls alone as well as with the IV. Table D.6 shows the simple OLS produces similar results. Taken together, these parameter estimates quantitatively link the reduced-form and structural analyses: the results align closely with the event-study patterns documented earlier, providing a natural bridge to the full model validation that follows.

Table 4: Market Access Structural Estimation

	$Log(Crime_d)$	$Log(Legitimate_d)$	$Log(Wages_d)$	$Log(Crime_o)$	$Log(Legitimate_o)$	$Log(Wages_o)$	$Log(Rent_o)$
				Panel A: Borusyak and Hull (2023)			
$Log(FMA^c)$	0.696***	-2.674***	-0.438***	-1.386**	-0.0896	-0.774***	-1.087***
	(0.215)	(0.747)	(0.126)	(0.619)	(0.543)	(0.233)	(0.271)
$Log(FMA^\ell)$		5.635***	0.737***	2.553	2.106	2.283***	2.282***
		(1.192)	(0.185)	(1.838)	(1.431)	(0.630)	(0.788)
$Log(CMA^c)$				-2.006*	-1.131	0.0200	0.341
				(1.182)	(0.874)	(0.282)	(0.242)
$Log(CMA^\ell)$				2.199	0.117	-0.900*	-0.817
				(2.045)	(1.628)	(0.504)	(0.586)
				Panel B: IV estimation			
$Log(FMA^c)$	0.744***	-3.050***	-0.491***	-2.263***	-0.398	-0.981***	-1.493***
	(0.212)	(0.804)	(0.143)	(0.791)	(0.679)	(0.280)	(0.315)
$Log(FMA^\ell)$		6.192***	0.813***	4.913**	3.023*	2.878***	3.339***
		(1.264)	(0.209)	(2.248)	(1.747)	(0.751)	(0.929)
$Log(CMA^c)$				-1.550	-1.152	-0.171	0.144
				(1.447)	(1.042)	(0.385)	(0.315)
$Log(CMA^\ell)$				0.317	-0.280	-0.852	-0.919
				(2.596)	(2.049)	(0.695)	(0.698)
Observations	538	538	525	410	538	490	538
F-stat first stage	38209	1810	1414	244	241	109	241
Expected MA	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Tables show neighborhood outcomes as functions of Firm and Commuter market access for 2007 and 2010. Outcomes used in regressions come from the rescaled data. Panel A, Borusyak and Hull (2023), controls for expected market access. For Panel B, we use predicted market access terms, holding fixed the initial number of residents and workers by sectors, as instruments; and further control for expected market access. In all specifications, we control for communa and year fixed effects. Standard errors clustered at neighborhood level reported in parentheses.

Under our general specification with all own- and cross-sector spillovers, theory leaves signs and magnitudes ambiguous, so the empirical coefficients are informative.

For instance, a negative coefficient of CMA^c on legitimate workers at the origin indicates that greater access to crime reduces legitimate workers in a neighborhood – via direct access to crime and negative residential externalities (from living with criminals). By contrast, a positive coefficient of FMA^c on criminal employment at destinations implies that criminal enterprises hire more when their access to workers increases.

Notably, suppose spillovers of legitimate workers on the legitimate sector were small (emphasizing the potential impact of criminal spillovers), then the model yields strong predictions: a negative effect of FMA^c on legitimate workers (at origin and destination) and rents. The estimates are consistent with this pattern: we find significant coefficients with matching signs for legitimate sectors at the destination and rents, and matching signs for legitimate workers at the origin. We interpret this as evidence of the importance of allowing for criminal spillovers in the structural model. While informative, the current exercise depends on approximations, that are relaxed in the next section as we estimate the full model to perform a set of powerful counterfactuals.

6 Parameter Estimation

We now estimate the structural elasticities and externalities—commuting, labor supply, residential choice, and cross-sector interactions using panel variation from network changes, gang conflicts, and shocks. Accordingly, we include an additional time index t. Our model delivers directly estimable specifications for sector-specific commuting elasticities, the sectoral labor supply elasticity, the residential choice elasticity, and cross-sectoral externalities. Identification is challenging because estimating equations reflect equilibrium relationships with unobserved amenities and productivities. We resolve these challenges with fixed effects and instruments capturing exogenous shocks. Our strategy deliberately draws on several different exogenous sources—network rollouts, the Don Berna shock, and shift-share industry shocks—so that no single source of variation drives identification.

Sector-Specific Commuting Elasticities. Following the literature, iceberg commuting is an exponential function of commute times:

$$\tau_{od,t} = \exp\left(\delta \text{time}_{od,t}\right) \ ,$$

where $\text{time}_{od,t}$ is the average travel time in minutes across public and private transportation modes of moving from o to d in period t.

Because we observe worker flows across neighborhoods for both sectors, and

Equation 5 gives sectoral commuting probabilities of commuting to destination d conditional on living in origin o and working in sector s, we derive the gravity equation linking commuting flows to iceberg costs

$$\log\left(\pi^{s}_{od|os,t}\right) = \underbrace{\beta^{s}}_{-\theta^{s}\cdot\delta} \cdot \text{time}_{\ od,t} + \gamma_{o,t} + \gamma_{d,t} + \gamma_{od} + \tilde{\epsilon}_{ods,t} \tag{12}$$

$\pi^{s}_{od|os,t}$ is the share commuting from o to d in sector s in year t. $time_{od,t}$ is the average commuting time. $\gamma_{o,t}$ are origin-time and $\gamma_{d,t}$ are destination-time fixed effects. γ_{od} are origin-destination comuna fixed effects, and $\tilde{\epsilon}_{ods,t}$ is an error term.

We leverage the rollout of the transit lines to derive exogenous variation in $time_{od,t}$, and so, Equation 12 does not relate two equilibrium objects. As we observe variation across origin-destination pairs over time, we address the confounders using fixed effects (as is standard). The origin-time fixed effects address unobserved residential neighborhood amenity shocks, and the destination-time fixed effects address unobserved destination-specific productivity shocks, including changes to the local economy, policing, and gang wars. The comuna pair fixed effects account for time-invariant features of the locations. Identification comes from changes in commute times between origin-destination pairs, over time.

We recover θ^{s}, given β^{s} and δ, using PPML to include zero commuting flows (Table 2). Using $\delta = 0.01$ from the literature (Tsivanidis, 2023; Zárate, 2023), we estimate criminal commuting elasticity $\hat{\theta}^{c} = 6.76$ and legitimate sector commuting elasticity $\hat{\theta}^{\ell} = 3.86$. Criminal workers are relatively more sensitive to commute times, similar to low-skill or informal workers in Latin America, given similarly lower levels of education (Tsivanidis, 2023; Zárate, 2023). Given that crime is illegal, and often localized, it is also plausible that criminal workers are even more sensitive to commuting times.

Sectoral Labor Supply Elasticity κ, Endogenous Residential Amenities ψ, ω. We estimate sectoral labor-supply elasticities from the ratio of labor supply by sector (as derived in Appendix E.1):

$$\begin{aligned}\Delta \log\left(\frac{R^{\ell}_{ot}}{R^{c}_{ot}}\right) &= \alpha_t + \psi \Delta \log L^{\ell}_{ot} + \omega \Delta \log L^{c}_{ot} \\ &\quad + \kappa \Delta \left[\frac{1}{\theta^{\ell}} \log\left(CMA^{\ell}_{ot}\right) - \frac{1}{\theta^{c}} \log\left(CMA^{c}_{ot}\right)\right] + \Delta X_{ot} + \tilde{u}_{ot}\ ,\end{aligned} \tag{13}$$

where Δ denotes within-neighborhood changes from t to $t-1$, α_t are year fixed effects, and X_{ot} are additional controls including comuna fixed effects, and transport-network exposure controls (per Borusyak and Hull 2023). $\tilde{u}_{ot}$ is the error. We instrument the difference in commuter market access using transport-time shocks that hold baseline populations fixed, ensuring the first stage reflects only changes in network geometry and resulting transport time.

Residential Choice Elasticity η. From the origin neighborhood choice probability in Equation 5, we obtain the residential-choice estimation equation (Appendix E.2):

$$\Delta \ln \pi_{o,t} = \eta \Delta(\ln W_{o,t} - (1-\beta) \ln Q_{o,t}) + \gamma_t + \Delta \tilde{X}_{ot} + \tilde{\epsilon}_{\eta,t} \ , \tag{14}$$

We set $1-\beta = 0.25$ (Ahlfeldt et al., 2015). γ_t are year-fixed effects, and $\tilde{X}_{ot}$ are additional controls constructed according to Borusyak and Hull (2023) aggregating across market access terms according to Equation 6. $\tilde{\epsilon}_{\eta,t}$ is the error term.

Productivity Externality λ. To estimate the crime externality parameter λ, we follow Ahlfeldt et al. (2015) and derive moment conditions using the structural productivity residual (as shown in Appendix E.3):

$$\Delta log\left(\frac{a^{\ell}_{d,t}}{\overline{a}^{\ell}_{t}}\right) = (\alpha^{\ell}+\zeta-1)\Delta log\left(\frac{q^{\ell}_{d,t}}{\overline{q}^{\ell}_{t}}\right) - (\alpha^{\ell}+\zeta)\Delta log\left(\frac{w^{\ell}_{d,t}}{\overline{w}^{\ell}_{t}}\right) - \lambda \Delta log\left(\frac{Y^{c}_{d,t}}{\overline{Y}^{c}_{t}}\right) \ , \tag{15}$$

where $\overline{a}^{\ell}_{t}$, $\overline{q}^{\ell}_{t}$, $\overline{w}^{\ell}_{t}$, $\overline{Y}^{c}_{t}$ are geometric means defined as $\overline{x_t} = exp(\frac{1}{S}\sum_{d=1}^{S} log(x_{dt}))$ and Δ removes time-invariant aspects of productivity, so Equation 15 has mean 0. The implied moment condition is:

$$\mathbb{E}\left[h(Z)\Delta log\left(\frac{a^{\ell}_{dt}}{\overline{a}^{\ell}_{t}}\right)\right] = 0 \ , \tag{16}$$

where $h(Z)$ is the vector of instruments discussed below.

Identification. Equations 13, 14, and 15 all require exogenous variation in equilibrium sectoral labor supply or transport times to be properly identified. Identification uses three exogenous sources: predicted changes in commuter market access from transit-line additions (transport times), a Bartik shift-share shock, and Don Berna's May 2008 extradition. Intuitively, the Bartik shock shifts legitimate labor supply, the Don Berna instrument shifts criminal labor supply, and transit lines affect market access. We use all three instruments jointly in Equation 13, the transit time shock for Equation 14, and Don Berna for Equation 15. As such, identification comes from within-neighborhood, over-time changes in access and costs, while instruments isolate plausibly exogenous shocks to travel times and opportunities. The exclusion restrictions are intuitive: Bartik shifts city-wide labor demand by industry mix (orthogonal to neighborhood-specific supply shocks), Don Berna shifts criminal labor locally without directly changing formal wages conditional on fixed effects, and transport-time shocks alter access but not amenities or productivities directly.

Shift-share/ Bartik Shocks: Bartik shocks help identify ψ, the endogenous legitimate-sector residential-amenity effect, as local legitimate-amenity varies with neighborhood legitimate-sector workers. Industry-level productivity shocks (derived from differential industry wage growth in cities outside Medellín) shift citywide labor demand while remaining orthogonal to local supply. Differences in baseline industry mix across neighborhoods create variation in exposure to these shocks (Borusyak et al., 2022). We discuss how we construct these instruments in Appendix E.4.

Don Berna Extradition: We exploit turf wars, after drug lord Don Berna's extradition, to identify criminal-labor related coefficients ω, λ. In Medellín, street gangs are under larger gang leaders. When gang lords are no longer in control, other gangs fight for the turf, leading to spikes in crime. After Pablo Escobar was killed in the early 1990s, Don Berna became the head of the Medellín Cartel, inheriting 4000 men under his command, drug-trafficking and exporting routes, gang alliances, and bribed police.[24]

In the early 2000s, Berna's attempts to consolidate more power resulted in a gang war, followed by the demobilization of his armed wing in 2003 and arrest in 2005. After his arrest, he continued to conduct all his activities from prison, including controlling the cocaine flow to the US. The US DEA insisted on his extradition, triggering a turf war between Maximiliano Bonilla, alias 'Valenciano, and Ericcson Vargas Cardona, alias 'Sebastián', to obtain Berna's territorial control. Under these disputes, the 'invisible frontiers', separated sets of blocks in a neighborhood, were created.

Don Berna's extradition was unanticipated: as the El Espectador (2008) newspaper put it (translated): "*surprisingly, early this morning the government lifted the extradition suspension against the demobilized leaders and ordered their immediate extradition to the US.... In total, there were 40 people handed over to the American government.*" Consistent with this interpretation, event-study pre-trends are flat in former Berna neighborhoods, and the

[24] Berna began his career with the Popular Liberation Army in the 1970s. He became involved with drug cartels after becoming the bodyguard of 'El Negro', an Escobar partner. After Escobar escaped from prison, Berna (with the help of the Cali Cartel) created 'Los Pepes' to hunt Escobar.

post-shock rise is concentrated in crimes linked to turf disputes, supporting its use as a criminal-labor shifter.

Figure D.8 shows a spike in homicides in former Don Berna neighborhoods, relative to all other neighborhoods. The raw pre-trends are parallel. Other crimes (property crime, extortion) also rose, lowering local firm functioning and residential amenities (Rozo, 2018; Sviatschi, 2022). Figure D.9 shows event study evidence of negative effects on the legitimate sector: rents and wages fell more in Don Berna areas.

Transport Times: We construct transport-time-based instruments (for Equations 13 and 14), by computing "adjusted" CMAs that: a) fix residents by origin and workers by destination for each sector at 2007 levels, but b) update transport times with new transit lines. We aggregate using the same formulas in Equations 13 and 14. For Equation 13, we use the adjusted log CMA difference as an instrument for actual differences in CMAs. For Equation 14, we plug our adjusted CMAs into $W_{o,t}$ (Equation 6).

This isolates exogenous variation from initial transport- time changes, excluding endogenous post-adjustments. Neighborhood fixed effects absorb time-invariant selection, and time effects absorb common shocks. We also believe that the timing of when lines are built and become operational is plausibly exogenous. Plans for the North-South metro line were drawn up in the 1980s, but the line itself was not inaugurated until 1995.[25] Fixed effects and the timing of lines address potential concerns about the location and operationalization of new lines.

Results. Interpreting the estimated elasticities through the model maps each parameter to a distinct margin—commuting frictions, sectoral labor demand, and residential sorting—so we can later decompose counterfactual welfare. Table 5 reports estimation results. Using GMM, we estimate crime productivity externality $\hat{\lambda} = -0.188$ (col. 3). Comparable production-agglomeration estimates are 0.242 (Bogotá; Tsivanidis 2023) and 0.07 (Berlin; Ahlfeldt et al. 2015). Although those capture positive agglomeration, they also originate from Ahlfeldt et al. (2015)'s specifications, and have similar scale. The magnitude similarities underscore the importance of modeling negative crime externalities. We use a value of $\zeta = 0.242$, based on Tsivanidis (2023)'s closely related work in Colombia, suggesting the crime productivity externality is nearly 80% as large as the positive agglomeration externality.

We estimate amenity effects $\hat{\omega} = -0.148$ (crime) and $\hat{\psi} = 0.524$ (legitimate sector)

[25] Sources: Department of National Planning (1982a)"Projecto Tren Metropolitano De Medellín Conpes Policy Document No. 1886.

Table 5: Estimating $\kappa, \omega, \psi, \eta, \lambda$

	(1)	(2)	(3)
	κ, ω, ψ	η	λ
	Log (Legitimate/Criminal)$_o$	Log(Residents)$_o$	Log(Productivity)$_d$
$\text{Log}(CMA^{\ell}_{ot})^{\frac{1}{\theta^{\ell}}} - \text{Log}(CMA^{c}_{ot})^{\frac{1}{\theta^{c}}}$	3.071**		
	(1.253)		
Log $Welfare_o$ – Log$Rent_o^{(1-\beta)}$		1.011*	
		(0.597)	
Log Criminal Labor$_o$	-0.148**		-0.188***
	(0.068)		(0.083)
Log Legitimate Labor$_o$	0.524***		
	(0.044)		
Observation Level	Neighborhood-Year	Neighborhood-Year	Neighborhood
Method	GMM	IV	GMM
Instrument(s)	Adj. CMA, Don Berna, Bartik	Adjusted CMA	Don Berna
F-Stat (of IV)	15.797	275.712	
Fixed Effects	Comuna, Year	Year	
Time Differenced	Yes	Yes	No
Observations	2,152	2,152	260
SE Cluster	Yes	Yes	Destination

Notes: Table estimates additional parameters. Log (Legitimate/Criminal) is the log of the ratio of (a) the number of legitimate-sector residents in a neighborhood, and (b) the number of criminal residents in a neighborhood. Log(Residents) is the natural log of the total number of residents in a neighborhood. The outcome and independent variable in the last column are demeaned by their geometric means across neighborhoods (Details in Appendix E.3). We report standard errors clustered at neighborhood level in parenthesis. "Time Differenced" refers to whether the specification was run differencing variables in period t from those in $t-1$. * Indicates significance at 10% level, ** indicates significance at 5% level, *** Indicates significance at 1% level.

in column 1. There is no close literature match for crime-amenity, but benchmarks for neighborhood agglomeration are 0.414–0.576 from (Tsivanidis, 2023). Again, our novel negative crime residential amenity is roughly 1/3 the magnitude of the legitimate sector residential amenity, indicating it is economically significant in this setting.

We estimate sector-choice elasticity $\hat{\kappa} = 3.071$ (col. 1), comparable to 2.0–3.6 in Zárate (2023) between formal/informal work. Residential-choice elasticity $\hat{\eta} = 1.011$ (col. 2), is similar to the 1 estimated in Tsivanidis (2023) and adopted in Zárate (2023).

Criminal Labor Share and Criminal Demand Elasticity. Lacking prior estimates, we set $\sigma^c = 6$ (Hottman et al., 2016) and $\alpha^c = 0.9$.[26] We show robustness in Appendix C.2.

[26]Changes in Criminal FMA shifts criminal labor supply. As shown in Appendix B.3.1, the coefficient that relates criminal workers to Criminal FMA informs criminal labor demand, which depends on the criminal demand elasticity (σ^c) and criminal labor share (α^c). The coefficients consistent with our estimates imply a large criminal demand elasticity (σ^c) and criminal labor share (α^c) lending support to the values used in the baseline model.

Shares of Residential and Commercial Floorspace. Finally, we take some parameters from the literature. Specifically, $(1-\beta), (1-\alpha^{\ell})$ are the share of residential floor space in consumer expenditure and the share of commercial floor space in firm costs, respectively. These are set following Ahlfeldt et al. (2015) to $\beta = 0.75$, $\alpha^{\ell} = 0.8$.

Extensions and Robustness Checks. Appendix C shows robustness to different extensions. Appendix C.2 confirms robustness to changes in parameter values. Appendix C.3 extends the amenity externality specifications and finds quantitatively similar results. In Appendix C.4, we extend the model to treat SISBEN workers and non-SISBEN workers as different types of workers to ensure our rescaling does not drive results. Results remain qualitatively and quantitatively consistent.

Validation Checks. Finally, we provide model validation tests. We evaluate how our predicted outcomes changes concord with the actual data for the tram line, Cable J, and the bus transit system.[27] Figure D.13 compares baseline levels and D.14 shows predicted changes. While there were numerous unmodeled concurrent shocks, our model reasonably predicts changes in crime. Table D.7 shows that our model predicts changes in incomes and rental rates as well. Table D.8 performs an additional exercise, where we estimate our market access regressions within the model, and compare coefficients to the data. The coefficients have the same sign and similar magnitude. While not a validation test, Figure D.7 also supports the log-linear gravity assumptions by plotting semi-parametric relationships between commuting and travel time.

7 Policy Counterfactuals

With these parameters in hand, we next simulate policy-relevant changes in the transit network and commuting costs to quantify sectoral reallocation, crime participation, and welfare effects. We ask: How do transport investments affect sectoral choice? Do new links import opportunity or export crime? Which neighborhoods should be prioritized for transit investments?[28]

We first focus on two real-world network-based counterfactuals. We then examine which neighborhoods should be targeted, by reducing the average commute time at each origin, and analyzing the welfare and criminality consequences. Finally, we assess the Auxilio de Transporte subsidy to the formal sector.

[27] We do not yet have enough post-period data for the northwestern Cable P.

[28] We solve the model using hat algebra as described in Appendix B.5. Given a lack of data on neighborhood income shares by factor, we assume that the owners of fixed factors are absentee and do not consume goods locally.

Equilibrium Effects of Recent Network Lines. We evaluate two transit lines built after our data: the Northwest Cable Line P (2021) and the 2015 Eastern Tram. Both served poor, crime-prone neighborhoods. Table 6 reports predicted effects on sectoral choice (and criminality), welfare, and the contribution of crime externalities.

Table 6: Counterfactuals: The Effects of Cable Line P and the Tram

Component	Cable P	Tram
%Δ Share Legitimate (avg)	0.0227	0.0033
%Δ Share Crime Origin (avg)	-1.0027	-0.0452
%Δ Welfare	1.5206	0.1852
%Δ GDP	.2048	0.0015
%$\Delta\tau$ (avg.)	-1.252	-0.1722
Contribution to Welfare (% of Hulten + Externalities)		
Crime Externalities	32.126	6.708
Sector	30.179	35.39
Commuting+Residential	1.947	-28.682

Notes: This table shows the counterfactual effects of Cable P and the Tram Line. Main outcomes are the change in welfare, GDP (sum of factor payments, discounted 10%, costs upfront), the share of legitimate sector workers, crime, and a decomposition of the criminal externality effects. The contribution of the crime externality effects to welfare, are presented as a fraction of the direct transport cost effect ("Hulten") and the externality effect. "Sector" describes the crime externality contribution through changing sector ('import of opportunity'), while "Commuting+Residential" describes the contribution through changing commuting and residential patterns. Decomposition details in Appendix B.4.

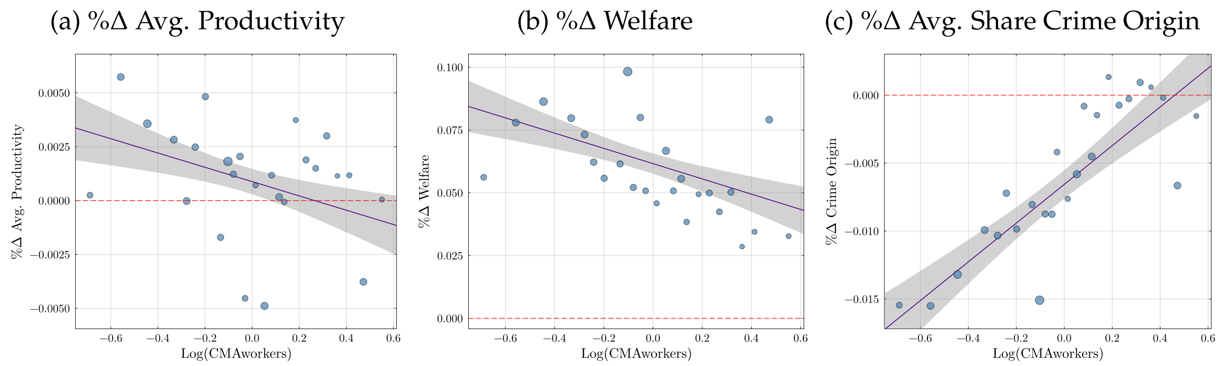
The new lines reduce the average probability of becoming a criminal by as much as 1%, an effect that is larger for Cable P than the tram, likely as Cable P has larger impacts on commute times (% $\Delta\tau$), since it connects more remote neighborhoods. Figure D.10 shows the changes in crime vs commute times by neighborhood. A lack of pre-existing public transportation likely drives the substantial impacts in the northwest. The tram has smaller, localized effects, given the east already had a bus network.

Relatedly, remote neighborhoods, lacking legitimate job access, benefit most. Figure D.11 shows, for the cable, the largest reductions in criminal participation happen close to the new stations (the 'import of opportunity'). Figure D.11 shows that remaining criminals shift activity (the destinations of crime) to more profitable areas in downtown, and the northeast –an 'export of crime.' Thus, the two maps show that there is both an import of opportunity, and an export of crime to neighborhoods farther away.

We evaluate the net change in welfare due to the new lines (assuming no migration to/from Medellin). Overall welfare rises: 0.185% for the tram, and 1.52% for Cable P (Table 6). Crime externalities explain between 6.7% and 32.1% of the welfare changes induced by the direct impacts of transport cost reductions and criminal externalities.[29] The advantage of our framework is we can decompose these contributions into sector choice and residential/commuting choice (details in Appendix B.4). For both lines, sector choice is a key driver.

Which Neighborhoods Should Be Targeted? The heterogeneity in impacts suggests that connecting certain neighborhoods is better than others. Which targeted neighborhoods are likely to produce the best city-level outcomes? We cut commute times in each origin o by 10%, one at a time.[30] Reductions in commuting costs for o residents affect all other neighborhoods, as it changes crime and legitimate-sector activity all over the city. We create city-level resident-weighted averages as outcomes.

Figure 7: Reduce Commute Costs by Neighborhood: By Baseline Legitimate CMA



Notes: Scatter plots show the relationship between changes in city-level outcomes against the baseline legitimate-sector CMA for treated origin o, where treatment is a ten percent reduction in commute costs ($\tau'_{od} = 0.9\tau_{od}\ \forall\ d$). X-axis is the legitimate-sector CMA of the neighborhood that receives the transport subsidy. Panel (a) shows the city-level average legitimate sector productivity. Panel (b) shows welfare, and Panel (c) shows city-level average crime rates (i.e., $\sum_o P(crime|origin)xPopulation_o$).

Figure 7 has a clear message: targeting low-CMA neighborhoods yields the largest reductions in citywide crime and gains in aggregate welfare and productivity. Indeed, treating most neighborhoods would reduce crime and improve welfare. Yet, there are exceptions: city-level crime rises (and productivity falls) when commute costs are lowered in certain already well-connected neighborhoods. Welfare generally improves, but crime externalities could, in theory, lead transit improvements to reduce welfare.

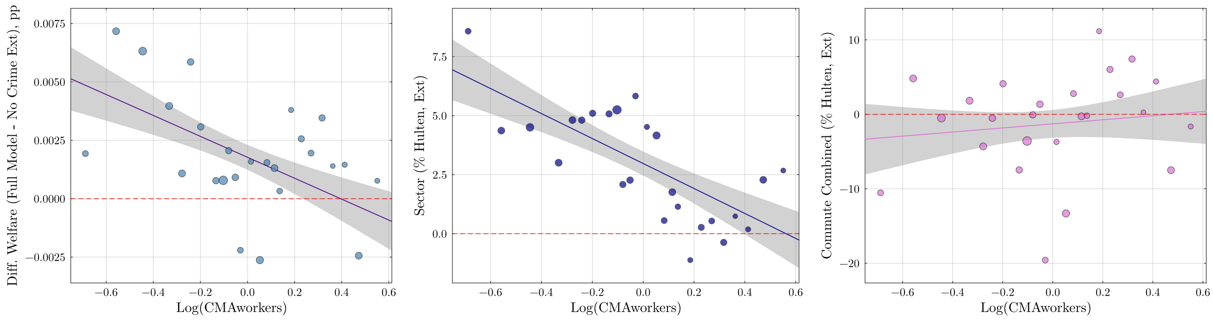
Figure 8 unpacks the crime externality contributions to welfare, mediated through changes in sector choice (middle panel) and commuting decisions and residential choice (right panel). The left panel shows how the effect of commute costs on welfare changes

[29]We report these percentages as a fraction of the sum of the direct effect of changes to transit times ("Hulten") and the externality effects.

[30]For each o, $\tau'_{od} = 0.9\tau_{od}\ \forall\ d$. This mimics taxi or ride-share subsidies.

Figure 8: Reducing Commute Costs by Each Neighborhood: Decomposition

(a) Crime Externality & Welfare (b) Sector Choice Contribution (c) Commuting and Residential



Notes: Scatter plots show the relationship between changes in city-level decomposition outcomes against the baseline legitimate-sector CMA for the treated origin o, where treatment is a ten percent reduction in commute costs ($\tau'_{od} = 0.9\tau_{od}\ \forall\ d$).

because of crime externalities. On the vertical axis, we plot the difference in welfare between the model with and without crime externalities. The crime externality tends to improve welfare in neighborhoods poorly connected at baseline (low CMA), by shifting workers to the legitimate sector (middle panel). Yet, in well-connected areas, crime externalities lead to welfare losses, given limited benefits from sector choice.

Overall, the vast majority of neighborhoods see gains in welfare through crime externalities arising from reductions in commute costs, with larger gains in low CMA areas (consistent with the 'import of opportunity.') However, changes in commuting and residential patterns can potentially 'export crime' such that welfare falls overall when reducing commuting costs for some neighborhoods.

Figure D.12 adds nuance to the decomposition. The top panels show crime externalities are a substantial share of welfare and correlate with baseline market access. The middle and bottom panels highlight sector choice is key, generally boosting welfare when commute times fall. These results underscore the role of crime externalities

The Auxilio de Transporte Program. We conduct a new counterfactual of a popular policy meant to help workers commute by providing a lump sum (approximately 10% of the minimum wage) to all workers earning less than twice the minimum wage. In practice, the program is not earmarked for commuting. It applies only to formal firms, effectively subsidizing the legitimate sector.

Appendix C.1 extends the model to quantify its welfare effects using destination-level coverage data, by simulating removal of the subsidy. The program boosts legitimate employment and yields welfare gains, however, the program is also rather costly at about 4% of GDP. Finally, the program is also progressive: crime falls most in low-CMA neighborhoods, where low-wage earners live (Figure C.2).

8 Discussion

Most cities around the world display stark segregation of activities across neighborhoods (Chetty and Hendren, 2018; Chyn, 2018; Jacob, 2004; Kling et al., 2007; Melnikov et al., 2022). The spatial distribution of criminal activity and legitimate-sector employment are interlinked by neighborhood segregation and access to different neighborhoods. Connecting neighborhoods provides access to economic opportunity and affects the occupation choices made by youth (Becker, 1968). Changes to transit networks meaningfully affect these relationships in a manner that changes the overall levels of crime and legitimate-sector employment in cities like Medellín.

We study the commuting behavior of criminals and legitimate workers, as it relates to economic opportunity. Doing so requires access to detailed geo-located data on where workers and criminals live and work, and a robust framework to isolate the effect of transit networks on crime and legitimate-sector jobs. Our quantitative spatial general equilibrium framework allows us to examine not only how access to opportunity affects the levels of criminal activity, but also the geographic spread of such activity to different neighborhoods. Both reduced form and structural estimates show that improving access to jobs in economically segregated parts of the city can substantially lower crime rates in high-crime environments. Despite some spread of criminal activity to different neighborhoods as a result of connecting segregated regions, simulations using the quantified model show that aggregate crime, welfare, and productivity of the city can often be improved by increasing the connectedness of most neighborhoods (with the exception of a few).

Nevertheless, neighborhoods in major cities across the world block expansions to transit infrastructure. Our paper provides a possible explanation for this opposition: the 'export of crime' to wealthier neighborhoods. Indeed, while we document substantial improvements to crime rates when expanding transportation, wealthier neighborhoods may block these expansions, given the spread of crime destinations that we document. The spatial distribution of gains may then determine whether or not transportation infrastructure is expanded, as small increases in crime rates in a few wealthy parts of the city may be particularly salient.

Moreover, our model builds on the urban quantitative literature by studying the general equilibrium consequences of crime, a crucial negative consequence of density in cities (Bryan et al., 2020; Glaeser and Sims, 2015), on city-level outcomes. As we show in our counterfactuals, on average, reducing commute costs across neighborhoods is welfare-enhancing, and effects are larger when connecting poorer and more segregated neighborhoods, as it provides workers in these neighborhoods with access to profitable, legitimate employment in the center of the city. Yet, our counterfactuals also show that not accounting for the negative externalities brought forth by crime can lead one to misstate the effects of reducing commute costs in some neighborhoods; for example, both overestimating welfare gains when crime spreads even minimally to high income and productive areas and under estimating welfare gains as the crime externalities amplify gains in neighborhoods with reductions in criminal activity.

Indeed, the exploration of crime within a framework of transportation infrastructure provides additional nuances for policy, over and above the political economy of opposition to expansions. As crime may have negative externalities to legitimate sector activity, it may not necessarily always be beneficial to reduce transit costs in all neighborhoods. Yet, even in the extremely high-crime and segregated setting of Medellín, most neighborhoods can be welfare-improving targets of transit expansions. We show that these expansions should be particularly targeted to neighborhoods with less legitimate sector access at baseline, even if they suffer from high criminal activity.

References

Ahlfeldt, G. M., Redding, S. K., Sturm, D. M., and Wolf, N. (2015). The Economics of Density: Evidence from the Berlin Wall. *Econometrica*, 83(6):2127–2189.

Almagro, M. and Domínguez-Iino, T. (2022). Location sorting and endogenous amenities: Evidence from Amsterdam. *University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2022-162, Available at SSRN 4279562*.

Athey, S., Ferguson, B., Gentzkow, M., and Schmidt, T. (2020). Experienced Segregation. *NBER Working Paper 27572*.

Baird, A. (2011). Negotiating Pathways to Manhood: Violence Reproduction in Medellin's Periphery. *Thesis, University of Bradford*.

Becker, G. S. (1968). Crime and punishment: An economic approach. In *The Economic Dimensions of Crime*, pages 13–68. Springer.

Bennett, P. and Ouazad, A. (2018). Job displacement, unemployment, and crime: Evidence from Danish microdata and reforms. *Journal of the European Economic Association*.

Billings, S. B. and Burkardt, E. B. W. (2011). Crime and the design of public transit systems. *Journal of Public Economics*, 95(1-2):18–25.

BJS, U. B. o. J. S. (1994). Sourcebook of Criminal Justice Statistics. *University at Albany*.

Blattman, C., Duncan, G., Benjamin, L., and Tobon, S. (2018). Gangs of Medellín: How Organized Crime is Organized. *Working Paper*.

Blattman, C., Duncan, G., Lessing, B., and Tobón, S. (2022). Gang rule: Understanding and countering criminal governance. *University of Chicago, Becker Friedman Institute for Economics Working Paper No. 85*.

Borusyak, K. and Hull, P. (2023). Nonrandom exposure to exogenous shocks. *Econometrica*, 91(6):2155–2185.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share designs. *Review of Economic Studies*, 89(1):181–213.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: Robust and efficient estimation. *The Review of Economic Studies*, 91(6):3253–3285.

Britto, D. G., Pinotti, P., and Sampaio, B. (2022). The Effect of Job Loss and Unemployment Insurance on Crime in Brazil. *Econometrica*, 90(4):1393–1423.

Bryan, G., Glaeser, E., and Tsivanidis, N. (2020). Cities in the developing world. *Annual Review of Economics*, 12:273–297.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Capone, D. L. and Nichols Jr, W. W. (1976). Urban structure and criminal mobility. *American Behavioral Scientist*, 20(2):199–213.

Card, D., Mas, A., and Rothstein, J. (2008). Tipping and the dynamics of segregation. *The Quarterly Journal of Economics*, 123(1):177–218.

CCSPJP (2009). Consejo Ciudadano para la Seguridad Publica y la Justicia Penal.

Cerdá, M., Morenoff, J. D., Hansen, B. B., Tessari Hicks, K. J., Duque, L. F., Restrepo, A., and Diez-Roux, A. V. (2012). Reducing violence by transforming neighborhoods: a natural experiment in Medellín, colombia. *American journal of epidemiology*, 175(10):1045–1053.

Chetty, R. and Hendren, N. (2018). The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics*, 133(3):1107–1162.

Chyn, E. (2018). Moved to opportunity: The long-run effects of public housing demolition on children. *American Economic Review*, 108(10):3028–56.

Cutler, D. and Glaeser, E. (1997). Are Ghettos Good or Bad? *Quarterly Journal of Economics*, 112(3).

David C., P. and Danielle, S. (2015). Does public transit spread crime? evidence from temporary rail station closures. *Regional Science and Urban Economics*, 52:13–26.

Davis, D. R., Dingel, J. I., Monras, J., and Morales, E. (2019). How segregated is urban consumption? *Journal of Political Economy*, 127(4):1684–1738.

de Chaisemartin, C. and D'Haultfœuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Dell, M., Feigenberg, B., and Teshima, K. (2019). The Violent Consequences of Trade-Induced Worker Displacement in Mexico. *American Economic Review: Insights*, 1(1):43–58.

Department of National Planning (2015). System for the identification of potential beneficiaries of social programs: Census of potential beneficiaries of subsidies in Colombia. Technical report, Government of Colombia, Bogota, Colombia.

Dingel, J. and Tintelnot, F. (2020). Spatial Economics for Granual Settings. *NBER Working Paper No. 27287*.

DiTella, R., Galiani, S., and Schargrodsky, E. (2010). Crime distribution and victim behavior during a crime wave. In *The economics of crime: Lessons for and from Latin America*, pages 175–204. University of Chicago Press.

Dix-Carneiro, R., Soares, R. R., and Ulyssea, G. (2018). Economic shocks and crime: Evidence from the Brazilian trade liberalization. *American Economic Journal: Applied Economics*, 10(4):158–95.

Donaldson, D. (2018). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*, 108(4-5):899–934.

Donaldson, D. and Hornbeck, R. (2016a). Railroads and American economic growth: A "market access" approach. *The Quarterly Journal of Economics*, 131(2):799–858.

Donaldson, D. and Hornbeck, R. (2016b). Railroads and american economic growth: A "market access" approach. *The Quarterly Journal of Economics*, 131(2):799–858.

Doyle, C. (2016). Explaining Patterns of Urban Violence in Medellin, Colombia. *Laws*, 5(3).

Ehrlich, I. (1973). Participation in illegitimate activities: A theoretical and empirical investigation. *Journal of Political Economy*, 81(3):521–565.

F.B.I (2020). Crime in the united states 2019. Technical report, Federal Bureau of Investigation, Washington.

Fu, C. and Wolpin, K. I. (2017). Structural estimation of a Becker-Ehrlich equilibrium model of crime: Allocating police across cities to reduce crime. *The Review of Economic Studies*, 85(4):2097–2138.

Georges-Abeyie, D. E. and Harries, K. D. (1980). *Crime: A spatial perspective*. Columbia University Press.

Gibbons, S. (2004). The costs of urban property crime. *The Economic Journal*, 114(499):F441–F463.

Glaeser, E. and Sims, H. (2015). Contagion, crime, and congestion: overcoming the downsides of density. *IGC Growth Brief*.

Greg, R. and John M., M. (2017). Effect of rail transit on crime: A study of los angeles from 1988 to 2014. *Journal of Quantitative Criminologys*, 33:277—-291.

Heblich, S., Redding, S. J., and Sturm, D. M. (2020). The making of the modern metropolis: evidence from London. *The Quarterly Journal of Economics*, 135(4).

Heblich, S., Trew, A., and Zylberberg, Y. (2021). East-side story: Historical pollution and persistent neighborhood sorting. *Journal of Political Economy*, 129(5):1508–1552.

Hottman, C. J., Redding, S. J., and Weinstein, D. E. (2016). Quantifying the sources of firm heterogeneity *. *The Quarterly Journal of Economics*, 131(3):1291–1364.

Ihlanfeldt, K. (2007). Neighborhood Drug Crimes and Young Males Job Accessibility. *The Review of Economics and Statisticsc*, 89(1):151–164.

Jacob, B. A. (2004). Public housing, housing vouchers, and student achievement: Evidence from public housing demolitions in Chicago. *American Economic Review*, 94(1):233–258.

Judicial Research Unit of the Metropolitan Police of the Aburrá Valley (2016). Census of all individuals arrested in Medellin 2006-2015. Technical report, Government of Colombia, Medellin, Colombia.

Kearney, M. S., Harris, B., Jacome, E., and Parker, L. (2014). Ten Economic Facts about Crime and Incarceration in the United States. *The Hamilton Project Policy Memo*. Brookings Institute.

Khanna, G., Medina, C., Nyshadham, A., Posso, C., and Tamayo, J. A. (2021). Job loss, credit and crime in Colombia. *American Economic Review: Insights*, 3(1):97–114.

Khanna, G., Medina, C., Nyshadham, A., Tamayo, J., and Torres, N. (2023). Formal employment and organized crime: Regression discontinuity evidence from Colombia. *The Economic Journal*, 133(654):2427–2448.

Kling, J. R., Liebman, J. B., and Katz, L. F. (2007). Experimental analysis of neighborhood effects. *Econometrica*, 75(1):83–119.

Medina, C. and Tamayo, J. (2011). An Assessment of How Urban Crime and Victimization Affects Life Satisfaction. *in Dave, Webb and Eduardo, Wills-Herrera (Eds.), Subjective Well-Being and Security*. Springer, Social Indicators Research Series.

Melnikov, N., Schmidt-Padilla, C., and Sviatschi, M. M. (2022). Gangs, labor mobility, and development: The role of extortion in el Salvador. *National Bureau of Economic Research*, 27832.

Ministry of Health (2019). The Integrated Registry of Contributions for all formal workers (PILA). Colombian Administrative Records for Social Security Payments 2008-2018. Technical report, Government of Colombia, Bogota, Colombia.

Rose, E. (2020). The Effects of Job Loss on Crime: Evidence from Administrative Data. *Working Paper, Available at SSRN 2991317*.

Rossi-Hansberg, E., Sarte, P.-D., and Owens III, R. (2010). Housing externalities. *Journal of Political Economy*, 118(3):485–535.

Rozema, R. (2018). Urban DDR-processes: Paramilitaries and Criminal Networks in Medellin, Colombia. *Journal of Latin American Studies*, 40:423–452.

Rozo, S. V. (2018). Is murder bad for business? Evidence from Colombia. *Review of Economics and Statistics*, 100(5):769–782.

Straulino, D., Saldarriaga, J. C., Gómez, J. A., Duque, J. C., and O'Clery, N. (2022). Uncovering commercial activity in informal cities. *Royal Society Open Science*, 9(11).

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

Sviatschi, M. M. (2022). Making a narco: Childhood exposure to illegal labor markets and criminal life paths. *Econometrica*, 90(4):1835–1878.

Tsivanidis, N. (2023). The aggregate and distributional effects of urban transit infrastructure: Evidence from Bogota's TransMilenio. *Conditionally Accepted at American Economic Review*.

United Nations Office on Drugs and Crime (UNODC) (2011). The transatlantic cocaine market.

Zárate, R. D. (2023). Factor allocation, informality and transit improvements: Evidence from Mexico City. *Policy Research Working Paper Series 9990, The World Bank*.

A Data Construction and Statistics

A.1 Administrative Data

The administrative data described hereafter is confidential and can only be stored and accessed in person in a fully secured location at the Central Bank of Colombia.

A.1.1 SISBEN

The SISBEN (Sistema de Identificación de Potenciales Beneficiarios de Programas Sociales) data comprise around 70 percent of the poorest people in Colombia. The survey is collected to identify and classify individuals and families according to their living conditions with the aim of making them beneficiaries of social programs. We use three waves of SISBEN carried out in 2002, 2005, and 2010. For each wave, we have the identification number of the individual, the neighborhood where the individual lives, if the individual is currently working, and the type of social security (subsidized or contributory) used to identify informal workers, among other individual characteristics. For the analysis, we keep individuals participating in the SISBEN survey at Medellín. That means that we have 1,166,232 individuals in SISBEN 2002, 1,493,832 individuals in SISBEN 2005, and 1,549,364 in SISBEN 2010.

A.1.2 PILA

We use information from the *Planilla Integrada de Liquidación de Aportes* (PILA). The PILA is the Colombian platform for making the monthly Social Security payment to workers. In most cases, this payment is made by the companies. We have access to the anonymized information of workers between 2008 and 2018. This database contains monthly-level information on wages, the number of working days, and an anonymized identifier of the firm that makes the payment.

A.1.3 Cámara de Comercio de Medellin

We use data on formally registered firms of Medellin. The entity that registers the firms in Medellin is the *Camara de Comercio de Medellin*. We have 80,268 firms on average by year between 2007 and 2016 with addresses. Nevertheless, most of them, 68.7%, are repeated across years. Among the non-repeated firms and non-repeated addresses, we have 257,391 standardized addresses that we geocode. We successfully geocode 87.3% of the addresses. On average, we have information on 3,027 firms by neighborhood for 268 neighborhoods. For each firm, we have the identification number of the legal representatives by year. We merge this identification with the PILA to obtain the match between the NIT (Colombian identification of the firm) and the anonymized identification of firms in PILA. This allows us to capture 33,312 firms in 8 years, representing 81% of formal workers in Medellin.

A.1.4 Crime Data

We use data from the census of people captured for the Aburra Valley Region (Valle de Aburrá). The data comes from the judicial research unit of the Metropolitan Police of the Aburra Valley Region (SIJIN). The data contains information on the identification number of arrested individuals, the neighborhood where the crime took place, the date of arrest, the criminal group (or gang) the individual belongs to, and the type of crime. We have 343,167 crimes reported between 2002 and 2015. We geocode 321,339 neighborhoods (the 93,6% of the total neighborhoods in the database). For these geocoded neighborhoods, we know that 84% of crimes were committed in Medellin and 16% in other Municipalities. To obtain the origin neighborhoods of these crimes committed in Medellín we merge the identification number of the criminal with SISBEN databases. Since we only have origin neighborhoods for individuals living in Medellín and not other regions, we match 63% of arrests to individuals living in the main part, and 78% when including the broader metro area.

A.1.5 Land Registry Data

We use cadastral records of Medellin from 2013 to 2018. The unit of observation is the property, that has information on address, neighborhood where it is located, price and area of the property, and the type of property (Commercial, Industrial, or Residential). On average, we have 2625 properties by neighborhood and 687,609 properties by year.

A.1.6 Informal Establishments

We obtain data on informal establishments from Straulino et al. (2022). The analysis uses machine vision techniques. The researchers manually label a set of google street view images, and train their model on this, before predicting the number of establishments for the full sample. It does not provide a count of the number of employees.

A.1.7 Encuesta de Calidad de Vida Data

We use household survey records of Medellin from 2004 to 2016. The unit of observation is the individual surveyed in that household that has information about employment status, social security payment, income, rental rate, schooling, and neighborhood where the household is located. On average, we have 9051 individuals by neighborhood-year.

A.2 Data Rescaling for Model Counterfactuals

As described in the main body of the paper, we combine different data sources to obtain information on the behavior of criminal and legitimate workers in Medellin. While very detailed, some of these sources are not censuses and hence do not capture all residents or workers within the city.[31] This section describes how we combine our data

[31] For example the SISBEN captures 70% of the population in Medellin.

sources with the Population Census in Medellin as well as with information on criminal probability of arrests so as to obtain a representative picture of sectoral composition of residents by origin and employment composition by sector at destination.[32]

Specifically, we need data on the number of workers and residents by sector-neighborhood $\{L_d^s, R_d^s\}$, $s \in \{\ell, c\}$. Our data provides information on:

1. Total counts of formal and informal employment by destination: $L_d^\ell = L_d^f + L_d^i$ from PILA and from Straulino et al. (2022).

2. Total counts of captured criminals by destination: L_d^c (from our arrests data)

3. Total counts of criminal residents by origin R_o^c (a combination of our arrests and Sisben data) and total counts of residents by origin from the population census R_o.

4. Commute flows for formal and criminal workers.

Scaling SISBEN Resident Counts to Census Resident Counts. The SISBEN surveys a fraction of the whole population in a neighborhood. Specifically, SISBEN surveys a share s_o, of the total residents in that neighborhood. Letting $R_o = R_o^{Census}$ be the true number of residents in neighborhood o, we observe:

$$R_o^{Sisben} = s_o R_o.$$

We can estimate s_o taking the ratio of the SISBEN residents and the Population Census, which contains information on the total residents by neighborhood R_o^{Census}, in 2005.

Estimating probability of criminals being arrested by destination p_d. The true number of criminals working in a location is the sum of the number of criminals that were arrested plus those that were not $L_d^c = L_d^{c,A} + L_d^{c,NA}$, where $L_d^{c,A}$ refers to the number of arrested criminals, which we observe, while $L_d^{c,NA}$ refers to the non-arrested criminals, which we do not observe. We assume that the probability of capture is location-specific and given by p_d so that:

$$L_d^{c,A} = p_d L_d^c.$$

To measure the probability of being captured, we use the share of homicides in a neighborhood that resulted in an arrest. Because homicides are typically reported, this provides a reliable measure of the fraction of homicides that were actually captured. Using this proxy for the probability of capture, we can then infer the total number of criminal

[32] In Section C.4, we describe an extension of the model that does not rely on this data procedure as a robustness check and find quantitatively and qualitatively similar results.

workers by destination as:

$$L_d^c = \frac{L_d^{c,A}}{p_d}. \tag{17}$$

To reduce concerns about measurement error, we compute p_d as the average ratio of captured individuals to homicides committed in neighborhood d from 2003 to 2015.

Scaling crime to get the total number of criminals by origin, R_o^c. To obtain the number of criminal residents by neighborhood, we use the fact that we can match arrest records to the SISBEN. In principle:

$$R_o^c = R_o^{c,Sisben} + R_o^{c,NonSisben},$$

where R_o^c is the total number of criminal residents in origin o, $R_o^{c,Sisben}$ is the number of criminal residents matched in SISBEN, and $R_o^{c,NonSisben}$ is the total number of residents not matched in SISBEN.

We argue that $R_o^{c,NonSisben} \approx 0$ because SISBEN covers the poorest 70% of households, who are more likely to participate in crime, while richer households are less likely to be involved. For example, the arrest rate for the wealthiest individuals within the SISBEN population (SISBEN score above 75) is only 1.8%. Therefore, the matched number of criminals to the SISBEN represents a reasonable approximation of the total number of criminals by origin.

$$R_o^c = R_o^{c,Sisben}. \tag{18}$$

Scaling legitimate workers to get the total number of workers by origin, R_o^ℓ. The number of residents in origin o can be decomposed into the criminal residents of origin o and the legitimate workers in that neighborhood: $R_o = R_o^c + R_o^\ell$. From the discussion above:

$$R_o^{Sisben} = s_o R_o = s_o(R_o^c + R_o^\ell) \ ,$$

Also as discussed above we can obtain the number of criminal residents by summing across criminal commuters scaled by the probability of getting captured $R_o^c = \sum_d \frac{L_{od}^{c,Sisben}}{p_d}$, and hence obtain the true number of residents working in the legitimate sector of a neighborhood o as:

$$R_o^\ell = \frac{R_o^{Sisben}}{s_o} - R_o^c, \tag{19}$$

so that the total number of legitimate residents is the difference between the re-scaled population and the criminal residents.

Scaling data on Formal and Informal Employment by Destination. We have data on employment by destination of formal workers from PILA L_d^f and some information on the number of informal establishments by destination from Straulino et al. (2022). So, we can obtain:

$$L_d^\ell = L_d^f + L_d^i. \tag{20}$$

Assuming that informal establishments are owner-managed establishments. This gives us information on the number of workers by destination.

Commute Flows. Our data on formal and criminal commute flows allow us to estimate gravity equations and the underlying commute elasticities for formal and criminal workers. When performing counterfactuals, we need to deal with the fact that commute flows should account for all legitimate workers and also that they are consistent with the rescaled totals of workers by sector-destination and residents by origin-sector. To do so, we compute baseline commute flow shares for both the legitimate and criminal sectors, consistent with the gravity equations.[33,34]

Specifically, as described in Appendix B.1, given information on commute elasticities $\{\theta^\ell, \theta^c\}$, total counts of residents and workers by origin and destination, as well as commute costs τ_{od}, one can invert the data to obtain sectoral wages $\{w_d^c, w_d^\ell\}$ for all destinations d. In turn, given these data, together with commute costs and elasticities, we can obtain the commute shares for legitimate workers and criminals for all origin-destination pairs.

Adjustment when origin vs. destination sector totals do not match. Finally, the total number of residents and workers within sectors, even after these adjustments, will not necessarily match. From Equation 17 we have the total number of criminal workers by destination and from Equation 20 we have the total number of legitimate workers by destination. From Equation 18 we have the total number of criminal residents by origin and from Equation 19 we have the total number of legitimate residents by origin.

Suppose after all the adjustments, we find that

$$\sum_o R_o^s < \sum_d L_d^s,$$

[33] Our data does not contain information on commute flows for informal workers. We assume that informal workers' commute elasticity is the same as that of formal workers. This assumption is reasonable because, in a similar context, Zárate (2023) estimates a commute elasticity for formal and informal workers in Mexico City and finds a parameter value of 3.78 similar to our estimates in the Medellín context of 3.86.

[34] As shown in Figure D.7, commute flows for criminals and formal workers are consistent with a log-linear relationship between commute flows and distance, which provides credence to the usage of the gravity equation to describe commute patterns of workers in Medellín.

we do the following adjustment:

$$R_o^{s\prime} = \left(\frac{\sum_d L_d^s}{\sum_o R_o^s} \right) R_o^s \ ,$$

which implies $\sum_o R_o^{s\prime} = \sum_d L_d^s$.

Similarly, if after the adjustments, we find that

$$\sum_o R_o^s > \sum_d L_d^s,$$

we then do the following final adjustment:

$$L_d^{s\prime} = \left(\frac{\sum_o R_o^s}{\sum_d L_d^s} \right) L_d^s \ ,$$

which implies $\sum_d L_d^{s\prime} = \sum_o R_o^s$

A.3 Constructing Commute Times

In this section, we describe how we compute commute times for the public transport in Medellín. Travel times were computed using the Network analysis tool from ArcMap. For most of the transportation modes, we use data from the city's government.[35] We obtain private vehicle speed levels by street from OpenStreetMap. We additionally set the regular bus speed by an optimization process where we minimize the difference between our travel times and Google's times. The parameters of our network can be summarized in the next table.

Table A.1: Spatial Network Calibration

Transport parameters	**speed**
Train lines	40km/h
Tram	16km/h
Aerial cable	18km/h
Metroplus bus	16km/h
Regular bus	16km/h
Walking speed	5km/h
Train station stop time	15s
Bus station stop time	30s

For private transport (motorbikes and cars), we used the Microsoft Bing API in

[35]The speed parameters for the metro system can be found here https://www.metrodemedellin.gov.co/Portals/3/Images/Contenido/REVISTAS-OTROS/2014_nuestro-metro.pdf

real time since we were not using counterfactuals for private transport. We computed the private transport travel times between 7 am and 10 am, which covers the rush hour in the city.

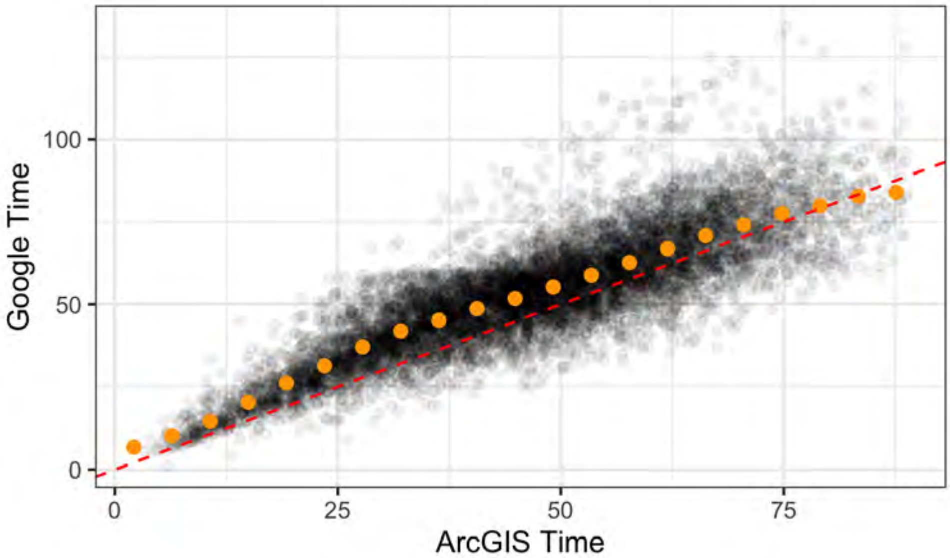
As robustness for our commuting times, we compare our results with the Google Maps API for public transport. We estimate a linear regression using a random sample of 10263 trips between different neighborhoods, obtaining an R-squared of 0.72, and a coefficient of 0.91. The results of the regression are represented in the next table:

Table A.2: ArcGis Time vs Google Time for public transport

	Dependent variable:
	Time Google
Time ArcGIS	0.906^{***}
	(0.006)
Constant	10.653^{***}
	(0.282)
Observations	10,263
R^2	0.715
Adjusted R^2	0.715
Residual Std. Error	9.854 (df = 10261)
F Statistic	$25{,}686.790^{***}$ (df = 1; 10261)
Note:	*p<0.1; **p<0.05; ***p<0.01

Total public minutes represent the travel times for public transport using ArcGIS, and Time represents travel times for public transport using the Google API. Ideally, one would expect the slope to be very close to one, as is our case. The following figure shows a binned scatter plot of these variables:

Figure A.1: Comparing Google-based and ArcGIS Commute Times (public transport)



Note: This figure compares travel times using the Google Api vs travel times using the ArcGIS network. The red line is the best-fit line, and the blue line is a 45 degrees line.

B Model Appendix

B.1 Sectoral Commuter and Firm Market Access

We define sectoral commuter market access as:

$$\mathrm{CMA}_o^s \equiv \sum_d \left(w_d^s\right)^{\theta^s} \left(\tau_{od}\right)^{-\theta^s}. \tag{21}$$

Using the definition of commuter market access, as well as commuter market clearing, we can write the number of workers in destination d, sector s as:

$$L_d^s = \left(w_d^s\right)^{\theta^s} \sum_o \frac{\left(\tau_{od}\right)^{-\theta^s}}{\mathrm{CMA}_o^s} R_o^s. \tag{22}$$

Similarly, we define Firm Market Access, which measures the degree to which firms in destination d have access to workers from sector s as:

$$\mathrm{FMA}_d^s \equiv \sum_o \frac{\left(\tau_{od}\right)^{-\theta^s}}{\mathrm{CMA}_o^s} R_o^s. \tag{23}$$

As discussed in Tsivanidis (2023); Zárate (2023), given information on commute elasticities, counts of workers by sector destination, and residents by origin sector, one can solve a system of equations to obtain sectoral commuter and firm market access.

Moreover, from equation 22 one can obtain sectoral wages as:

$$\left(w_d^s\right)^{\theta^s} = \frac{L_d^s}{\text{FMA}_d^s}.$$

B.2 Model Equilibrium

In this appendix, we show the main equations that define the equilibrium of the model, and we show that one can express the main variables of interest as a function of market access for infinitesimal changes in transportation costs.

The following equations characterize the equilibrium in the model:

1. Sectoral labor Demand

$$w_d^s = k_d^s \left(E^s\right)^{\frac{1}{\sigma^s}} \left(A_d^s\right)^{\frac{\sigma^s - 1}{\sigma^s}} \left(L_d^s\right)^{-\frac{1+\left(\sigma^s-1\right)\left(1-\alpha^s\right)}{\sigma^s}}, \tag{24}$$

where k_d^s is a constant that depends on parameters of the model and E^s is aggregate expenditure on sectoral varieties.[36]

2. Sectoral labor Supply:

$$L_d^s = \left(w_d^s\right)^{\theta^s} \text{FMA}_d^s \tag{25}$$

3. Sectoral Firm Market Access Definition:

$$\text{FMA}_d^s = \sum_o \tau_{od}^{-\theta^s} R_o^s \left(\text{CMA}_o^s\right)^{-1} \tag{26}$$

4. Residents by origin-sector

$$R_o^s = \Theta Q_o^{-\eta(1-\beta)} \left[\sum_s B_o^s \left(CMA_o^s\right)^{\frac{\kappa}{\theta^s}}\right]^{\frac{\eta-\kappa}{\kappa}} B_o^s \left(CMA_o^s\right)^{\frac{\kappa}{\theta^s}}. \tag{27}$$

where $\Theta \equiv \bar{L}\left(\gamma^{\eta} \bar{U}^{-\eta}\right) P^{-\eta\beta}$ is an endogenous constant and P is the aggregate price index within the city of the freely tradable goods.

5. Total Residents by origin:

$$R_o = \Theta Q_o^{-\eta(1-\beta)} \left[\sum_s B_o^s \left(CMA_o^s\right)^{\frac{\kappa}{\theta^s}}\right]^{\frac{\eta}{\kappa}}. \tag{28}$$

[36]Specifically, $E^s \equiv \left[\xi^s \sum_{o \in \mathcal{M}} \left(\frac{P_o C_o}{\left(P_o^s\right)^{1-\sigma^s}}\right) + \xi_F^s \frac{P_F C_F}{\left(P_F^s\right)^{1-\sigma^s}}\right]$ and $k_d^s \equiv \left(\alpha^s\right)^{\frac{1-\left(1-\alpha^s\right)\left(1-\sigma^s\right)}{\sigma^s}} \left(\frac{1-\alpha^s}{\bar{F}_d^s}\right)^{\frac{\left(1-\alpha^s\right)\left(1-\sigma^s\right)}{\sigma^s}}$.

6. Income per worker:

$$v_o = \left[\sum_s B_o^s \left(CMA_o^s\right)^{\frac{\kappa}{\theta^s}}\right]^{-1} \sum_s \sum_d B_o^s \left(CMA_o^s\right)^{\frac{(\kappa-\theta^s)}{\theta^s}} \tau_{od}^{-\theta^s} \left(w_d^s\right)^{\theta^s+1}. \tag{29}$$

7. Total Worker Income:

$$v_o R_o = \Theta Q_o^{-\eta(1-\beta)} \left[\sum_s B_o^s \left(CMA_o^s\right)^{\frac{\kappa}{\theta^s}}\right]^{\frac{\eta-\kappa}{\kappa}} \sum_s B_o^s \left(CMA_o^s\right)^{\frac{(\kappa-\theta^s)}{\theta^s}} \sum_d \tau_{od}^{-\theta^s} \left(w_d^s\right)^{\theta^s+1}. \tag{30}$$

8. Definition of sectoral commuter market access:

$$\text{CMA}_o^s = \sum_d \tau_{od}^{-\theta^s} \left(\text{FMA}_d^s\right)^{-1} L_d^s. \tag{31}$$

9. Rental rates:

$$Q_o = \frac{(1-\beta)}{\beta \bar{H}_o} \left[v_o R_o + \sum_s \frac{(1-\alpha^s)}{\alpha^s} w_o^s L_o^s\right]. \tag{32}$$

10. Amenity Externalities:

$$B_o^s = b_o^s \prod_{s'} (L_o^{s'})^{\omega^{s's}}. \tag{33}$$

11. Productivity Externalities:

$$A_d^s = a_d^s \prod_{s'} (L_d^{s'})^{\lambda^{s's}}. \tag{34}$$

B.3 Expressing Changes in Variables as a function of Changes in Market Access for Infinitesimal Changes in Transportation Costs

We use the baseline expression of the equilibrium equations to show that, under some conditions, one can express the changes in the main outcomes of the model as a function of changes in sectoral commuter and firm market access for infinitesimal shocks.[37]

1. From Equation 24, the log Derivative of Sectoral labor Demand

$$d \log w_d^s = \frac{1}{\sigma^s} d \log E^s + \left(\frac{\sigma^s - 1}{\sigma^s}\right) d \log A_d^s - \left(\frac{1 + (\sigma^s - 1)(1-\alpha^s)}{\sigma^s}\right) d \log \left(L_d^s\right) \tag{35}$$

[37]Specifically, as we note below, the first of these conditions is that commute shares are close to income shares, which we find is true in the data. Also, the system of equations requires an approximation around prohibitive transport costs.

Also note that the log-derivative of the wage bill is:

$$d \log w_d^s + d \log L_d^s = \frac{1}{\sigma^s} d \log E^s + \left(\frac{\sigma^s - 1}{\sigma^s}\right) d \log A_d^s - \left(\frac{1 + \sigma^s + (\sigma^s - 1)(1 - \alpha^s)}{\sigma^s}\right) d \log (L_d^s) \tag{36}$$

2. From Equation 25, the log derivative of sectoral labor Supply:

$$d \log L_d^s = \theta^s d \log (w_d^s) + d \log \text{FMA}_d^s \tag{37}$$

3. From Equation 27, the log derivative of Residents by origin-sector:

$$\begin{aligned} d \log R_o^s &= d \log \Theta - \eta(1-\beta) d \log Q_o \cdots \\ &+ (\eta - \kappa) \sum_s \pi_{o|o}^s \left[d \log B_o^s + \frac{1}{\theta^s} d \log CMA_o^s \right] + \kappa d \log B_o^s + \frac{\kappa}{\theta^s} d \log CMA_o^s \end{aligned} \tag{38}$$

4. From Equation 28, the log derivative of total residents by origin:

$$d \log R_o = d \log \Theta - \eta(1-\beta) d \log Q_o + \eta \sum_s \pi_{o|o}^s \left[d \log (B_o^s) + \frac{1}{\theta^s} d \log (CMA_o^s) \right] \tag{39}$$

5. From Equation 29, the log derivative of income per worker:

$$d \log v_o = \sum_s \sum_d \vartheta_{od|o}^s \left[d \log \pi_{o|o}^s + d \log \pi_{od|os}^s + d \log w_d^s \right]$$

where:

$$\vartheta_{od|o}^s \equiv \frac{\pi_{o|o}^s \pi_{od|os}^s w_d^s}{v_o}$$

is the share of total percapita worker in o coming from sector s destination d. Notice that, since:

$$d \log CMA_o^s = \theta^s \sum_d \pi_{od|os}^s d \log (w_d^s \tau_{od}^{-1}),$$

then, assuming that income shares are equal to commute shares and taking an approximation around $\tau_{od}^{-1} = 0 \quad \forall d \neq o$, we can express the change in residential income as a share-weighted average of the changes of sectoral commuter market access.

$$d \log v_o \approx \sum_s \pi_{o|o}^s \frac{1}{\theta^s} d \log CMA_o^s \tag{40}$$

Also note that under the same conditions:

$$d\log v_o R_o = (\eta+1)\sum_s \pi^s_{o|o}\frac{1}{\theta^s} d\log CMA^s_o - \eta(1-\beta) d\log Q_o + \cdots$$
$$\eta \sum_s \pi^s_{o|o} d\log\left(B^s_o\right) + d\log\Theta \tag{41}$$

6. From Equation 32, the log derivative of rental rates:

$$d\log Q_o = \chi^L_o d\log v_o R_o + \chi^H_o d\log Q_o + \sum_s \chi^s_o d\log q^s_o \tag{42}$$

where we define the shares of expenditure in housing as $\chi^W_o \equiv \frac{v_o R_o}{I_o}, \chi^H_o \equiv \frac{Q_o H_o}{I_o}, \chi^s_o \equiv \frac{q^s_o \bar{F}^s_o}{I_o}$: So that:

$$(1-\chi^H_o) d\log Q_o = \chi^W_o d\log v_o R_o + \sum_s \chi^s_o d\log(w^s_o L^s_o)$$

Plugging in Equation 41:

$$\left[(1-\chi^H_o) + \chi^W_o \eta(1-\beta)\right] d\log Q_o - \sum_s \chi^s_o d\log(w^s_d L^s_d) = \cdots$$
$$\cdots \chi^W_o (\eta+1)\sum_s \pi^s_{o|o}\frac{1}{\theta^s} d\log CMA^s_o + \chi^W_o \eta \sum_s \pi^s_{o|o} d\log\left(B^s_o\right) + \chi^W_o d\log\Theta \tag{43}$$

7. Amenity Externalities:

$$d\log B^s_o = d\log b^s_o + \sum_{s'} \omega^{s's} d\log L^{s'}_o$$

8. Productivity Externalities:

$$d\log A^s_d = d\log a^s_d + \sum_{s'} \lambda^{s's} d\log L^{s'}_d$$

Summarizing, we can use the previous equations to express the change in the number of workers and residents by sector, number of total residents, the rental rates, and the wages by sector implicitly as a function of changes in sectoral Commuter and

Firm Market Access as:

$$
\begin{aligned}
& -\theta^s\left(\frac{\sigma^s-1}{\sigma^s}\right) d\log A_d^s+\left[1+\theta^s\left(\frac{1+\left(\sigma^s-1\right)\left(1-\alpha^s\right)}{\sigma^s}\right)\right] d\log L_d^s \cdots \\
& \cdots=d\log \mathrm{FMA}_d^s+u_d^{L^s} \qquad (44)\\
& -\sum_s \chi_o^s\left(\frac{\sigma^s-1}{\sigma^s}\right) d\log A_d^s-\sum_s \chi_o^W \eta \pi_{o|o}^s d\log \left(B_o^s\right)+\cdots \\
& \sum_s \chi_o^s\left(\frac{1+\sigma^s+\left(\sigma^s-1\right)\left(1-\alpha^s\right)}{\sigma^s}\right) d\log \left(L_d^s\right)+\left[\left(1-\chi_o^H\right)+\chi_o^W \eta(1-\beta)\right] d\log Q_o \cdots \\
& \cdots=\chi_o^W(\eta+1) \sum_s \pi_{o|o}^s \frac{1}{\theta^s} d\log C M A_o^s+u_o^{Q_o} \qquad (45)\\
& -\eta \sum_{s^{\prime}} \pi_{o|o}^{s^{\prime}} d\log \left(B_o^{s^{\prime}}\right)+\eta(1-\beta) d\log Q_o+d\log R_o=\eta \sum_{s^{\prime}} \pi_{o|o}^{s^{\prime}} \frac{1}{\theta^{s^{\prime}}} d\log \left(C M A_o^{s^{\prime}}\right)+u_o^R \\
& \qquad (46)\\
& -(\eta-\kappa) \sum_{s^{\prime}} \pi_{o|o}^{s^{\prime}} d\log B_o^{s^{\prime}}-\kappa d\log B_o^s+\eta(1-\beta) d\log Q_o+d\log R_o^s=\cdots \\
& (\eta-\kappa) \sum_{s^{\prime}} \pi_{o|o}^{s^{\prime}} \frac{1}{\theta^{s^{\prime}}} d\log C M A_o^{s^{\prime}}+\frac{\kappa}{\theta^s} d\log C M A_o^s+u_o^{R_o^s} \qquad (47)\\
& d\log A_d^s=\sum_{s^{\prime}} \lambda^{s^{\prime} s} d\log L_d^{s^{\prime}}+u_d^{A_d^s} \qquad (48)\\
& d\log B_o^s=\sum_{s^{\prime}} \omega^{s^{\prime} s} d\log L_o^{s^{\prime}}+u_o^{B_o^s} \qquad (49)
\end{aligned}
$$

Stacking this system of equations by neighborhood and denoting the endogenous outcomes by $\boldsymbol{g}_j$ and the error terms by $\boldsymbol{u}_j$:

$$
d\log \boldsymbol{g}_{\boldsymbol{j}} \equiv\left[\begin{array}{l}
d\log L_j^1 \\
\cdots \\
d\log L_j^S \\
d\log Q_j \\
d\log R_j \\
d\log R_j^1 \\
\cdots \\
d\log R_j^S \\
d\log w_j^1 \\
\cdots \\
d\log w_j^S
\end{array}\right], d\log \boldsymbol{u}_{\boldsymbol{j}} \equiv\left[\begin{array}{l}
d\log u_j^{L^1} \\
\cdots \\
d\log u_j^{L^S} \\
d\log u_j^R \\
d\log u_j^Q \\
d\log u_j^{R^1} \\
\cdots \\
d\log u_j^{R^S} \\
d\log u_j^{w^1} \\
\cdots \\
d\log u_j^{w^S}
\end{array}\right] .
$$

We can express the outcomes in matrix notation as:

$$\mathbf{\Lambda} d\log \boldsymbol{g}_j = \sum_s \boldsymbol{b}_R^s d\log CMA_j^s + \sum_s \boldsymbol{b}_F^s d\log FMA_j^s + d\log \boldsymbol{u}_j.$$

Furthermore, if the matrix $\mathbf{\Lambda}$ is invertible, there is a reduced form representation:

$$d\log \boldsymbol{g}_j = \sum_s \boldsymbol{\beta}_{Rj}^s d\log CMA_j^s + \sum_s \boldsymbol{\beta}_{Fj}^s d\log FMA_j^s + d\log \boldsymbol{e}_j,$$

where $\boldsymbol{\beta}_{Rj}^s = \mathbf{\Lambda}^{-1}\boldsymbol{b}_{Rj}^s, \boldsymbol{\beta}_{Fj}^s = \mathbf{\Lambda}^{-1}\boldsymbol{b}_{Fj}^s, \boldsymbol{e}_j = \mathbf{\Lambda}^{-1} d\log \boldsymbol{u}_j$.

The reduced form coefficients are indexed by j because they depend both on structural parameters as well as in some cases on baseline characteristics of the neighborhoods such as the baseline share of residents that work in a specific sector.

B.3.1 Two Sector Example

The market access regressions are useful because, under some conditions, they can be informative about the sign and presence of cross sectoral externalities. To show this, we first note that, in a two sector model where crime has a negative externality on legitimate productivity, some of the market access coefficients can non parametrically be informative about the presence of these negative cross sectoral externalities.

We then show the reduced form coefficients of the market access regressions are in the full two sector model.

As in the main model, we assume that there are two sectors, a legitimate sector and a criminal sector $s \in \{\ell, c\}$. We allow for cross-sectoral externalities in productivity and amenities from the criminal sector to the legitimate sector.[38]

$$A_d^\ell = a_d^\ell \left(L_d^\ell\right)^\zeta \left(L_d^c\right)^\lambda$$
$$B_o^\ell = b_o^\ell \left(L_o^\ell\right)^\psi \left(L_o^c\right)^\omega,$$

Non-Parametric Proof of Negative Effect of FMA^c on FMA^ℓ With Negative Cross Sectoral Externalities. Let labor demand and labor supply to the legitimate sector be determined by the following functions

$$L_d^\ell = L_d^\ell \left(w_d^\ell, A_d^\ell\right)$$
$$w_d^\ell = w_d^\ell \left(L_d^\ell, FMA_d^\ell\right)$$

[38]Note that we use the parameter notation as in the main body of the text, by which positive agglomeration externalities of legitimate workers on legitimate productivity is parametrized by ζ and positive agglomeration externalities of legitimate workers on legitimate residents is parametrized by ψ.

From labor demand:

$$d\log L_d^\ell = \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell} d\log w_d^\ell + \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log A_d^\ell$$

From labor supply:

$$d\log w_d^\ell = \frac{\partial \log w_d^\ell}{\partial \log L_d^\ell} d\log L_d^\ell + \frac{\partial \log w_d^\ell}{\partial \log FMA_d^\ell} d\log FMA_d^\ell$$

Plugging in the second equation to the first equation:

$$d\log L_d^\ell = \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell} \left[\frac{\partial \log w_d^\ell}{\partial \log L_d^\ell} d\log L_d^\ell + \frac{\partial \log w_d^\ell}{\partial \log FMA_d^\ell} d\log FMA_d^\ell \right] + \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log A_d^\ell$$

We can write:

$$d\log A_d^\ell = \zeta d\log L_d^\ell + \lambda d\log L_d^c + d\log a_d^\ell.$$

So that:

$$\begin{aligned} &\left[1 - \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell} \frac{\partial \log w_d^\ell}{\partial \log L_d^\ell} - \zeta \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} \right] d\log L_d^\ell = \cdots \\ &\cdots \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell} \frac{\partial \log w_d^\ell}{\partial \log FMA_d^\ell} d\log FMA_d^\ell + \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} \lambda d\log L_d^c + \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log a_d^\ell. \end{aligned} \tag{50}$$

Suppose there is no productivity externality from the legitimate sector to the criminal sector. For the criminal sector:

$$\left[1 - \frac{\partial \log L_d^c}{\partial \log w_d^c} \frac{\partial \log w_d^c}{\partial \log L_d^c} \right] d\log L_d^c = \frac{\partial \log L_d^c}{\partial \log w_d^c} \frac{\partial \log w_d^c}{\partial \log FMA_d^c} d\log FMA_d^c + \frac{\partial \log L_d^c}{\partial \log a_d^c} d\log a_d^c.$$

So that:

$$d\log L_d^c = \beta^c d\log FMA_d^c + u_d^c, \tag{51}$$

where:[39]

$$\beta^c \equiv \frac{\frac{\partial \log L_d^c}{\partial \log w_d^c} \frac{\partial \log w_d^c}{\partial \log FMA_d^c}}{\left[1 - \frac{\partial \log L_d^c}{\partial \log w_d^c} \frac{\partial \log w_d^c}{\partial \log L_d^c} \right]} > 0.$$

[39] The error term is composed of changes of fundamental productivity in the criminal sector, $u_d^c \equiv \beta^c \frac{\partial \log L_d^c}{\partial \log a_d^c} d\log a_d^c$.

Since:

$$\underbrace{\frac{\partial \log L_d^c}{\partial \log w_d^c}}_{<0}\underbrace{\frac{\partial \log w_d^c}{\partial \log FMA_d^c}}_{<0} > 0, \quad \text{and} \quad \left[1 - \underbrace{\frac{\partial \log L_d^c}{\partial \log w_d^c}}_{<0}\underbrace{\frac{\partial \log w_d^c}{\partial \log L_d^c}}_{>0}\right] > 0.$$

Define:

$$\beta^\ell \equiv \left[1 - \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell}\frac{\partial \log w_d^\ell}{\partial \log L_d^\ell} - \zeta\frac{\partial \log L_d^\ell}{\partial \log A_d^\ell}\right]^{-1}.$$

From equation 50:[40]

$$d\log L_d^\ell = \beta^\ell \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell}\frac{\partial \log w_d^\ell}{\partial \log FMA_d^\ell} d\log FMA_d^\ell + \beta^\ell \lambda \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log L_d^c + u_d^\ell.$$

Plugging in equation 51, we can write this as a function of the other sectors FMA_d^c as:[41]

$$d\log L_d^\ell = \alpha^\ell \frac{\partial \log L_d^\ell}{\partial \log w_d^\ell}\frac{\partial \log w_d^\ell}{\partial \log FMA_d^\ell} d\log FMA_d^\ell + \lambda\beta^\ell\beta^c \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log FMA_d^c + e_d^\ell$$

Notice that, as long as ζ is sufficiently small, then $\beta^\ell > 0$, and thus the sign of the coefficient of FMA_d^c will be given by the sign of λ. If there is a negative externality of the criminal sector on the legitimate sector, the sign of $d\log FMA_d^c$ on $d\log L_d^\ell$ will be negative.

That is, if there is a negative externality of criminal activity on legitimate productivity, and agglomeration externalities in the legitimate sector are sufficiently small, then the coefficient of firm market access of the criminal sector on the number of workers in the legitimate sector will be negative.[42] This is true without taking a stance on the exact specification (log linear or not) of the externalities.

Reduced Form Coefficients in the Full Model. The non parametric argument above focuses on one of the market access regressions. We now derive all of the reduced form coefficients as a function of structural parameters and initial neighborhood characteristics:

[40]We define the error term as: $u_d^\ell \equiv \beta^\ell \frac{\partial \log L_d^\ell}{\partial \log A_d^\ell} d\log a_d^\ell$.

[41]The error in the reduced form representation is a combination of the errors in both the legitimate and criminal equations: $e_d^\ell \equiv \beta^\ell \lambda \beta^c u_d^c + u_d^\ell$.

[42]Our market access regressions show a positive sign of legitimate FMA on legitimate workers, which means that the conditions for this proof are satisfied empirically.

$$\left[1+\theta^{c}\left(\frac{1+\left(\sigma^{c}-1\right)\left(1-\alpha^{c}\right)}{\sigma^{c}}\right)\right] d\log L_{d}^{c}=d\log \mathrm{FMA}_{d}^{c}+u_{d}^{L^{c}}$$

$$\left[1+\theta^{\ell}\left(\frac{1+\left(\sigma^{\ell}-1\right)\left(1-\alpha^{\ell}\right)}{\sigma^{\ell}}\right)-\theta^{\ell}\left(\frac{\sigma^{\ell}-1}{\sigma^{\ell}}\right)\zeta\right] d\log L_{d}^{\ell}-\cdots$$

$$\cdots-\theta^{\ell}\left(\frac{\sigma^{\ell}-1}{\sigma^{\ell}}\right)\lambda d\log L_{d}^{c}=d\log \mathrm{FMA}_{d}^{\ell}+u_{d}^{L^{\ell}}$$

$$\left[\chi_{o}^{\ell}\left(\frac{\sigma^{\ell}-1}{\sigma^{\ell}}\right)\lambda-\chi_{o}^{c}\left(\frac{1+\left(\sigma^{c}-1\right)\left(1-\alpha^{c}\right)+\sigma^{c}}{\sigma^{c}}\right)+\chi_{o}^{W}\eta\pi_{o|o}^{\ell}\omega\right] d\log\left(L_{d}^{c}\right)+\cdots$$

$$\cdots-\left[\chi_{o}^{\ell}\left(\frac{1+\left(\sigma^{c}-1\right)\left(1-\alpha^{\ell}\right)+\sigma^{\ell}}{\sigma^{\ell}}\right)+\chi_{o}^{W}\eta\pi_{o|o}^{\ell}\psi\right] d\log\left(L_{d}^{\ell}\right)+\cdots$$

$$\cdots+\left[\left(1-\chi_{o}^{H}\right)+\chi_{o}^{W}\eta(1-\beta)\right] d\log Q_{o}=\chi_{o}^{W}\sum_{s}\pi_{o|o}^{s}\frac{1}{\theta^{s}}d\log CMA_{o}^{s}+u_{o}^{Q}$$

$$d\log R_{o}+\eta(1-\beta)d\log Q_{o}-\eta\pi_{o|o}^{\ell}\left(\omega d\log L_{o}^{c}+\psi d\log L_{o}^{\ell}\right)=\cdots$$

$$\cdots+\eta\sum_{s}\pi_{o|o}^{s}\frac{1}{\theta^{s}}d\log\left(CMA_{o}^{s}\right)+u_{o}^{R}$$

$$d\log R_{o}^{c}+\eta(1-\beta)d\log Q_{o}-(\eta-\kappa)\pi_{o|o}^{\ell}\left(\omega d\log L_{o}^{c}+\psi d\log L_{o}^{\ell}\right)=\cdots$$

$$\cdots+(\kappa-\eta)\pi_{o|o}^{\ell}\frac{1}{\theta^{\ell}}d\log CMA_{o}^{\ell}-\frac{1}{\theta^{s}}\left[\eta-\kappa\left(1-\pi_{o|o}^{c}\right)\right] d\log CMA_{o}^{c}+u_{o}^{R^{c}}$$

$$d\log R_{o}^{\ell}+\eta(1-\beta)d\log Q_{o}-\left[\eta\pi_{o|o}^{\ell}-\kappa(1-\pi_{o|o}^{\ell})\right]\left(\omega d\log L_{o}^{c}+\psi d\log L_{o}^{\ell}\right)=\cdots$$

$$\cdots+(\kappa-\eta)\pi_{o|o}^{c}\frac{1}{\theta^{c}}d\log CMA_{o}^{c}-\frac{1}{\theta^{\ell}}\left[\eta-\kappa\left(1-\pi_{o|o}^{\ell}\right)\right] d\log CMA_{o}^{\ell}+u_{o}^{R^{\ell}}$$

Defining $\tilde{\sigma}^{c}\equiv\sigma^{c}-1$ and $\tilde{\alpha}^{c}\equiv 1-\alpha^{c}, \tilde{\beta}=1-\beta$, the resulting reduced form coefficients for the number of criminal workers, legitimate workers, output, rental rates, total residents, criminal residents, legitimate residents, and wages are given by $\begin{bmatrix} L_{j}^{c} & L_{j}^{\ell} & Q_{j} & R_{j} & R_{j}^{c} & R_{j}^{\ell} & w_{j}^{\ell}\end{bmatrix}^{\top}$:[43]

[43] As in the counterfactuals, these coefficients assume owners of fixed factors consume their income outside of the city.

$$\boldsymbol{\beta}^{c}_{FMA} = \begin{bmatrix} \frac{\sigma^c}{\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c} \\ \frac{\lambda\sigma^c\tilde{\sigma}^\ell\theta^\ell}{(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ \frac{\eta(-1+\tilde{\sigma}^c)\pi^\ell_{o|o}(\omega(-1+\tilde{\sigma}^\ell)+(\omega+\psi\lambda\tilde{\sigma}^\ell-\omega\zeta\tilde{\sigma}^\ell+\omega\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)}{(1+\tilde{\beta}\eta)(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ \frac{\eta(-1+\tilde{\sigma}^c)\pi^\ell_{o|o}(\omega(-1+\tilde{\sigma}^\ell)+(\omega+\psi\lambda\tilde{\sigma}^\ell-\omega\zeta\tilde{\sigma}^\ell+\omega\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)}{(1+\tilde{\beta}\eta)(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ -\frac{(\kappa+\eta(-1+\tilde{\beta}\kappa))(-1+\tilde{\sigma}^c)\pi^\ell_{o|o}(\omega(-1+\tilde{\sigma}^\ell)+(\omega+\psi\lambda\tilde{\sigma}^\ell-\omega\zeta\tilde{\sigma}^\ell+\omega\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)}{(1+\tilde{\beta}\eta)(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ -\frac{(-1+\tilde{\sigma}^c)(-((1+\tilde{\beta}\eta)\kappa)+(\kappa+\eta(-1+\tilde{\beta}\kappa))\pi^\ell_{o|o})(\omega(-1+\tilde{\sigma}^\ell)+(\omega+\psi\lambda\tilde{\sigma}^\ell-\omega\zeta\tilde{\sigma}^\ell+\omega\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)}{(1+\tilde{\beta}\eta)(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ \frac{\lambda\sigma^c\tilde{\sigma}^\ell}{(\sigma^c+(1+\tilde{\alpha}^c\tilde{\sigma}^c)\theta^c)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \end{bmatrix}.$$

The rest of the coefficients are:

$$\boldsymbol{\beta}^{\ell}_{FMA} = \begin{bmatrix} 0 \\ \frac{\sigma^\ell}{\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell} \\ \psi\frac{\eta\sigma^\ell\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ \psi\frac{\eta\sigma^\ell\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ -\psi\frac{(\kappa+\eta(-1+\tilde{\beta}\kappa))(-1+\tilde{\sigma}^\ell)\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ \frac{\psi\sigma^\ell(\kappa+\tilde{\beta}\eta\kappa-(\kappa+\eta(-1+\tilde{\beta}\kappa))\pi^\ell_{o|o})}{(1+\tilde{\beta}\eta)(\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell)} \\ -\frac{1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell}{\sigma^\ell+(1-\zeta\tilde{\sigma}^\ell+\tilde{\alpha}^\ell\tilde{\sigma}^\ell)\theta^\ell} \end{bmatrix}, \quad \boldsymbol{\beta}^{c}_{CMA} = \begin{bmatrix} 0 \\ 0 \\ \frac{(1+\eta)\pi^c_{o|o}}{(1+\tilde{\beta}\eta)\theta^c} \\ -\frac{(-1+\tilde{\beta})\eta\pi^c_{o|o}}{(1+\tilde{\beta}\eta)\theta^c} \\ \frac{\eta-\tilde{\beta}\eta+(\kappa+\eta(-1+\tilde{\beta}+\tilde{\beta}\kappa))\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)\theta^c} \\ \frac{(\kappa+\eta(-1+\tilde{\beta}+\tilde{\beta}\kappa))(-1+\pi^\ell_{o|o})}{(1+\tilde{\beta}\eta)\theta^c} \\ 0 \end{bmatrix}, \quad \boldsymbol{\beta}^{\ell}_{CMA} = \begin{bmatrix} 0 \\ 0 \\ \frac{(1+\eta)\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)\theta^\ell} \\ -\frac{(-1+\tilde{\beta})\eta\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)\theta^\ell} \\ -\frac{(\kappa+\eta(-1+\tilde{\beta}+\tilde{\beta}\kappa))\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)\theta^\ell} \\ \frac{\kappa+\tilde{\beta}\eta\kappa-(\kappa+\eta(-1+\tilde{\beta}+\tilde{\beta}\kappa))\pi^\ell_{o|o}}{(1+\tilde{\beta}\eta)\theta^\ell} \\ 0 \end{bmatrix}.$$

Following a similar intuition as in the non-parametric case, the signs of the coefficients are informative of the sign of the externalities.

B.4 Welfare Effects Decomposition

In order to gauge the importance of the criminal externality components on welfare, we build on the fact that, as previous literature has shown (Tsivanidis, 2023; Zárate, 2023), spatial models are amenable to welfare decompositions whereby the change in aggregate city can be decomposed into different elements.

$$dlog\mathcal{W} = \text{Direct effects} + \text{Criminal externalities} + \text{Other terms}$$

Focusing on the criminal externalities components, in our model, these will be driven by changes in the number of criminal workers in the Destinations weighted by some welfare weights, specifically:

$$CriminalExternalities = \sum_d \Theta_d dlogL_d^c\ ,$$

where Θ_d represents the welfare weights.

Using the fact that the change in the number of criminals at a destination d is given by the baseline commute flow weighted averages of the changes in the number of residents in different locations, the number of individuals within those locations that choose a criminal sector, and the change in the share of individuals within those origins that become criminals that choose to commute to a particular destination.

$$dlogL_d^c = \sum_o \frac{L_{od}^c}{L_d^c} \left\{ \underbrace{d \log \pi_o}_{\text{Residents}} + \underbrace{d \log \pi_{od|oc}^c}_{\text{Commute}} + \underbrace{d \log \pi_{o|o}^c}_{\text{Sector}} \right\}$$

We can further decompose the criminal externalities into:

$$CriminalExternalities = \sum_d \Theta_d \sum_o \frac{L_{od}^c}{L_d^c} \left\{ \underbrace{d \log \pi_o}_{\text{Residents}} + \underbrace{d \log \pi_{od|oc}^c}_{\text{Commute}} + \underbrace{d \log \pi_{o|o}^c}_{\text{Sector}} \right\} \tag{52}$$

In the main body of the text, we use this equation to decompose criminal externalities into different components. And for different welfare weights, we compare the magnitude of the criminal externalities to the direct effects from urban transportation infrastructure investments. Specifically, we use as welfare weights the share of legitimate production destination and the share of total income in a particular origin.

B.5 Hat Algebra

Denoting the proportional change of a variable x across two different counterfactuals $\widehat{x} \equiv \frac{x'}{x}$, we can express the equilibrium of the model in Hat Algebra as follows:

Sectoral labor demand:

$$\hat{w}_d^s = \left(\hat{E}^s\right)^{\frac{1}{\sigma^s}} \left(\hat{A}_d^s\right)^{\frac{\sigma^s-1}{\sigma^s}} \left(\hat{L}_d^s\right)^{-\frac{1+(\sigma^s-1)(1-\alpha^s)}{\sigma^s}}$$

Aggregate expenditure in sector s is given by:

$$E^s \equiv \left[\xi^s \sum_o \left(\frac{P_o C_o}{\left(P_o^s\right)^{1-\sigma^s}} \right) + \xi_F^s \frac{P_F C_F}{\left(P_F^s\right)^{1-\sigma^s}} \right].$$

Since goods are tradable within the city and the wider economy $P_o^s = P^s \quad \forall o$. On the other hand, we allow the foreign price index, P_F^s, to differ from the domestic price index because, for example, foreign consumers may have access to additional varieties above and beyond the city-specific ones.

Assuming that both domestic as well as foreign consumers spend a share β on tradable goods:

$$E^s = \beta \left[\xi^s \frac{I_D}{(P^s)^{1-\sigma^s}} + \xi_F^s \frac{I_F}{\left(P_F^s\right)^{1-\sigma^s}} \right],$$

where we define total domestic income as $I_D \equiv \sum_{o \in \mathcal{M}} I_o$. Define:

$$\nu_D^s \equiv \frac{\xi^s \frac{I_D}{(P^s)^{1-\sigma^s}}}{\left[\xi^s \frac{I_D}{(P^s)^{1-\sigma^s}} + \xi_F^s \frac{I_F}{\left(P_F^s\right)^{1-\sigma^s}} \right]},$$

as the share of total expenditure in sector s that depends on domestic consumption.

Then:

$$\hat{E}^s = \nu_D^s \frac{\hat{I}_D}{\left(\hat{P}^s\right)^{1-\sigma^s}} + (1 - \nu_D^s) \frac{\hat{I}_F}{\left(\hat{P}_F^s\right)^{1-\sigma^s}}.$$

The change in domestic income is given by:

$$\hat{I}_D I_D = \sum_{o \in \mathcal{M}} \hat{I}_o I_o$$

The domestic sectoral price index is:

$$P^s = \left[\sum_d (p_d^s)^{1-\sigma^s} \right]^{\frac{1}{1-\sigma^s}}$$

So that:

$$\hat{P}^s = \left[\sum_{d \in \mathcal{M}} \frac{\left(p_d^s\right)^{1-\sigma^s}}{(P^s)^{1-\sigma^s}} (\hat{p}_d^s)^{1-\sigma^s} \right]^{\frac{1}{1-\sigma^s}}$$

Defining $s_d^s \equiv \frac{p_d^s c_d^s}{\sum_{o \in \mathcal{M}} P_o^s C_o^s}$ as the share of total domestic expenditure in sector s in goods coming from neighborhood d, then:

$$s_d^s = \frac{\left(p_d^s\right)^{1-\sigma^s}}{(P^s)^{1-\sigma^s}}.$$

The change in the sectoral price index is:

$$\hat{P}^s = \left[\sum_{d\in\mathcal{M}} s^s_d (\hat{p}^s_d)^{1-\sigma^s}\right]^{\frac{1}{1-\sigma^s}}$$

and the foreign price index is given by:

$$\hat{P}^s_F = \left[\sum_{d\in\mathcal{M}} \frac{\left(p^s_d\right)^{1-\sigma^s}}{(P^s_F)^{1-\sigma^s}} (\hat{p}^s_d)^{1-\sigma^s} + \sum_{f\notin\mathcal{M}} \frac{\left(p^s_f\right)^{1-\sigma^s}}{(P^s_F)^{1-\sigma^s}} (\hat{p}^s_f)^{1-\sigma^s}\right]^{\frac{1}{1-\sigma^s}}$$

Defining the foreign expenditure shares as $s^s_{Fd} \equiv \frac{p^s_d c^s_{dF}}{P^s_F C^s_F}$:

$$\hat{P}^s_F = \left[\sum_{d\in\mathcal{M}} s^s_{Fd} (\hat{p}^s_d)^{1-\sigma^s} + \sum_{f\notin\mathcal{M}} s^s_{Ff} (\hat{p}^s_f)^{1-\sigma^s}\right]^{\frac{1}{1-\sigma^s}}$$

The aggregate price index within the city is:

$$\hat{P} = \prod_s (\hat{P}^s)^{\xi^s}$$

The Sectoral labor supply:

$$\hat{L}^s_d = (\hat{w}^s_d)^{\theta^s} \, \hat{\text{FMA}}^s_d$$

Origin shares:

$$\hat{\pi}_o = \frac{\left(\hat{Q}_o\right)^{-\eta(1-\beta)} \left(\hat{W}_o\right)^{\eta}}{\sum_o \pi_o \left(\hat{Q}_o^{-(1-\beta)} \hat{W}_o\right)^{\eta}}$$

Note that:

$$\widehat{U} = \hat{P}^{-\beta\eta} \sum_o \pi_o \left(\hat{Q}_o^{-(1-\beta)} \hat{W}_o\right)^{\eta}$$

The change in the number of residents in o:

$$\hat{\pi}_o = \hat{P}^{-\beta\eta} (\hat{U})^{-1} \left(\hat{Q}_o\right)^{-\eta(1-\beta)} \left(\hat{W}_o\right)^{\eta}$$

where:

$$\hat{W}_o = \left[\sum_s \pi^s_{o|o} \left(\hat{B}^s_o\right) \left(C\hat{M}A^s_o\right)^{\frac{\kappa}{\theta^s}}\right]^{1/\kappa}.$$

Origin-Sector Shares:

$$\hat{\pi}^{s}_{o|o} = \frac{\hat{B}^{s}_{o}\left(\hat{W}^{s}_{o}\right)^{\kappa}}{(\hat{W}_{o})^{\kappa}},$$

and:

$$\hat{W}^{s}_{o} = \left(C\hat{M}A^{s}_{o}\right)^{\frac{1}{\theta^{s}}}.$$

Residents by origin-sector:

$$\hat{R}^{s}_{o} = \hat{Q}_{o}^{-\eta(1-\beta)}\left[\sum_{s}\pi^{s}_{o|o}\hat{B}^{s}_{o}\left(C\hat{M}A^{s}_{o}\right)^{\frac{\kappa}{\theta^{s}}}\right]^{\eta-\kappa}\left(\hat{B}^{s}_{o}\right)\left(C\hat{M}A^{s}_{o}\right)^{\frac{\kappa}{\theta^{s}}},$$

and residents by origin:

$$\hat{R}_{o} = \hat{P}^{-\beta\eta}(\hat{U})^{-1}\left(\hat{Q}_{o}\right)^{-\eta(1-\beta)}\left(\hat{W}_{o}\right)^{\eta}.$$

Income per worker:

$$\hat{v}_{o}v_{o} = \sum_{s}\sum_{d}\pi^{s}_{od|os}\pi^{s}_{o|o}w^{s}_{d}\hat{\pi}^{s}_{od|os}\hat{\pi}^{s}_{o|o}\hat{w}^{s}_{d},$$

with:

$$\hat{\pi}^{s}_{od|os} = \frac{\left(\hat{w}^{s}_{d}\hat{\tau}^{-1}_{od}\right)^{\theta^{s}}}{C\hat{M}A^{s}_{o}},$$

and:

$$C\hat{M}A^{s}_{o} = \sum_{d}\pi^{s}_{od|os}\left(\hat{w}^{s}_{d}\hat{\tau}^{-1}_{od}\right)^{\theta^{s}}$$

The change in sectoral shares is given by:

$$\hat{\pi}^{s}_{o|o} = \frac{\left(\hat{B}^{s}_{o}\hat{W}^{s}_{o}\right)^{\kappa}}{\left(\hat{W}_{o}\right)^{\kappa}}$$

Total income of workers in origin o is given simply by $\hat{v}_{o}\hat{R}_{o}$.

Rental rates:

$$\hat{Q}_{o} = \hat{v}_{o}\hat{R}_{o}$$

where we assume that only workers consume housing.

We solve the model assuming that the legitimate sector good is undifferentiated and freely tradable, that criminal firms income depends primarily on foreign demand, and that no neighborhood within the city is large enough to affect global prices of drugs.[44] We assume that owners of the specific factors and landlords are absentee and use their income outside of the city, so that:

$$\hat{I}_D = \sum_{o \in \mathcal{M}} \hat{v}_o \hat{R}_o \frac{v_o R_o}{\sum_o v_o R_o}$$

[44] That is $\sigma^\ell \to \infty$, $\nu^c_D = 0$, $s^c_{Fd} \to 0$.

C Model Extensions

C.1 Auxilio de Transporte

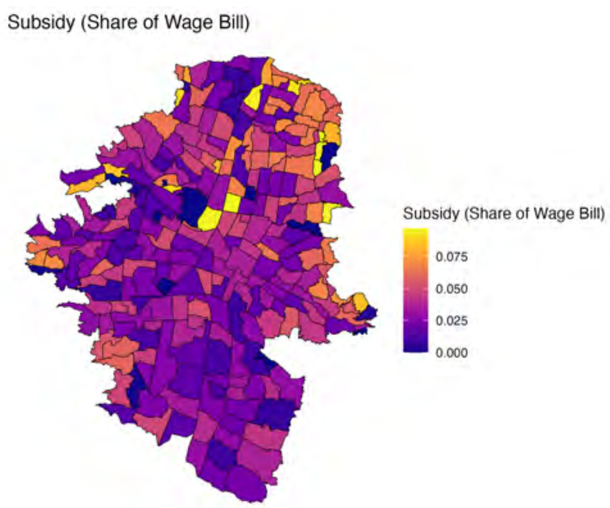
Auxilio de Transporte is a policy implemented by the Colombian government that provides a subsidy of approximately 10% of the minimum wage to all formal workers who earn less than two times the minimum wage. While the original intent of the policy was to subsidize workers' commuting, in practice, the subsidy does not have to be used for transportation. Given these institutional details, we model this policy as a wage bill subsidy for legitimate firms.

Using data on the number of workers who earn less than twice the minimum wage in each neighborhood, we measure the implied subsidy by neighborhood as follows. Denoting $\underline{w}$ the minimum wage and $\underline{L}_d$ as the total number of workers in location d earning less than twice the minimum wage, we obtain the destination level implied subsidy as a share of the wage bill using the following formula.

$$s_d = 0.1 \times \frac{\underline{w}\underline{L}_d}{WageBill_d}$$

Using data from PILA, we find that a sizable proportion of the population in Medellin, 63% of workers, earn less than twice the minimum wage. Figure C.1 shows the implied Subsidy as a Share of Wage Bill across Neighborhoods in Medellin. Given the magnitude of the policy, the total cost is substantial. We find that the total cost of the subsidies amounts to approximately 4% of the city's total legitimate wage bill.

Figure C.1: Subsidy as Share of Wage Bill



Notes: We obtain informal workers at the destination from the survey of informal establishments. To compute the number of formal workers by destination who earn less than twice the minimum wage, we use PILA between 2007 and 2016.

Welfare Effects of Auxilio de Transporte

Given the fact that the policy does not require workers or firms to use the subsidy for any specific use, particularly transportation, we model the policy as a subsidy to legitimate firms in each neighborhood.

Thus, the effective wage bill paid by legitimate firms at destination d is given by $w_d^\ell(1-s_d^\ell)L_d^\ell$

$$w_d^s(1-s_d^s)L_d^s = \alpha^s p_d^s y_d^s$$

so the subsidy is expressed as a share of the total wage bill.

The zero profits condition means that unit costs have to be equal to prices:

$$p_d^s = \frac{(w_d^s(1-s_d^s))^{\alpha^s}(q_d^s)^{1-\alpha^s}}{A_d^s}$$

The FOC of the other factor implies:

$$q_d^s \overline{F}_d^s = (1-\alpha^s)p_d^s y_d^s$$

In the case in which only legitimate firms face a subsidy and the legitimate good is freely tradable, the legitimate firm's FOCs can be described by:

$$\hat{q}_d^s = \hat{y}_d^s = \hat{A}_d^s \left(L_d^s\right)^{\alpha^s}$$

and from zero profits

$$\hat{A}_d^s = (\hat{w}_d^s)^{\alpha^s}\left(\widehat{[1-s_d^s]}\right)^{\alpha^s}(\hat{q}_d^s)^{1-\alpha^s}$$

or:

$$\hat{w}_d^s = \frac{\left(\hat{A}_d^s\right)^{\frac{1}{\alpha^s}}}{\widehat{[1-s_d^s]}}(\hat{q}_d^s)^{-\left(\frac{1-\alpha^s}{\alpha^s}\right)}$$

where:

$$\widehat{[1-s_d^s]} = \frac{1-(s_d^s)'}{1-s_d^s}$$

In particular, note that to evaluate the effect of a policy starting from a baseline of zero:

$$\widehat{[1-s_d^s]} = 1-(s_d^s)'$$

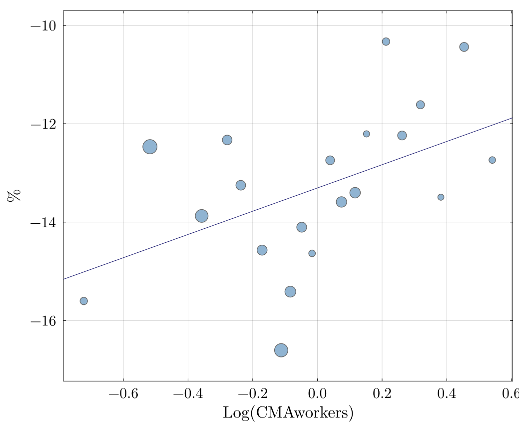
We assume that the taxes are funded through lump-sum taxation so that:

$$\sum_d s_d^\ell w_d^\ell L_d^\ell = T$$

Counterfactual. We evaluate the effects of the policy on city outcomes by comparing the economy without the subsidies versus the economy with the subsidies. The main outcomes are shown in Figure C.2.

Figure C.2: Welfare effects of subsidy policy

%Δ in Crime Rates



Aggregate Effects of Policy

Variable	Percent change
%Δ Welfare	4.8374
%Δ Gini Income p. Capita	-12.2235
%Δ Share Legitimate (average)	0.1695
%Δ Share Crime Origin (average)	-13.3961

Notes: The graph on the left shows the percent change in crime rates induced by the subsidies by different baseline log CMA for workers. The table on the right shows the aggregate effects of that policy for city level output.

The results show that the Auxilio de Transporte Policy is effective in reducing crime rates in the city as a whole, decreasing average crime rates by 13.4%. Moreover, the policy differentially benefits neighborhoods that have lower CMA for the legitimate sector at baseline, with the largest decreases in neighborhood crime rates in those neighborhoods. This likely reflects the fact that most low-wage workers live in low-CMA neighborhoods. In terms of aggregate effects, we find that the policy has large effects with a percent change increasing welfare of 4.83%. This is perhaps not surprising given the fact that this policy itself is very large. As mentioned before, the total cost of the subsidies amounts to approximately 4% of the city's total legitimate wage bill, making this a very large policy.

C.2 Different Parameter Values

In this section, we show that the main counterfactual results are robust to a varying the values of the parameters related to the criminal sector. In particular, we show that results are robust to different values of the demand elasticity of the criminal good and different values of the labor demand elasticity in the criminal sector. We also show the sensitivity of the results to the externalities specification in Appendix C.3.

Table C.1: Counterfactual effects for different α^c (labor share in criminal sector)

Group	Panel	%Δ Share Legitimate (average)	%Δ Share Crime Origin (average)	%Δ Welfare
$\alpha^c = 0.85$				
	Tram	0.0032	-0.0345	0.1846
	Cable P	0.0207	-0.8621	1.5043
$\alpha^c = 0.9$				
	Tram	0.0033	-0.0452	0.1852
	Cable P	0.0227	-1.0027	1.5206
$\alpha^c = 0.95$				
	Tram	0.0035	-0.058	0.186
	Cable P	0.0252	-1.1749	1.5405

Notes: This table shows the effects of the Tram and Cable P on the main variables of interest for different values of the parameter α^c which represents the labor share in the criminal sector.

Table C.2: Counterfactual effects for different σ^c (demand elasticity criminal sector)

Group	Panel	%Δ Share Legitimate (average)	%Δ Share Crime Origin (average)	%Δ Welfare
$\sigma^c = 4$				
	Tram	0.0031	-0.0271	0.1841
	Cable P	0.0194	-0.767	1.4933
$\sigma^c = 6$				
	Tram	0.0033	-0.0452	0.1852
	Cable P	0.0227	-1.0027	1.5206
$\sigma^c = 8$				
	Tram	0.0035	-0.0566	0.186
	Cable P	0.0249	-1.1559	1.5383

Notes: This table shows the effects of the Tram and Cable P on the main variables of interest for different values of the parameter σ^c which represents criminal good demand elasticity.

C.3 Amenity Externalities Specification

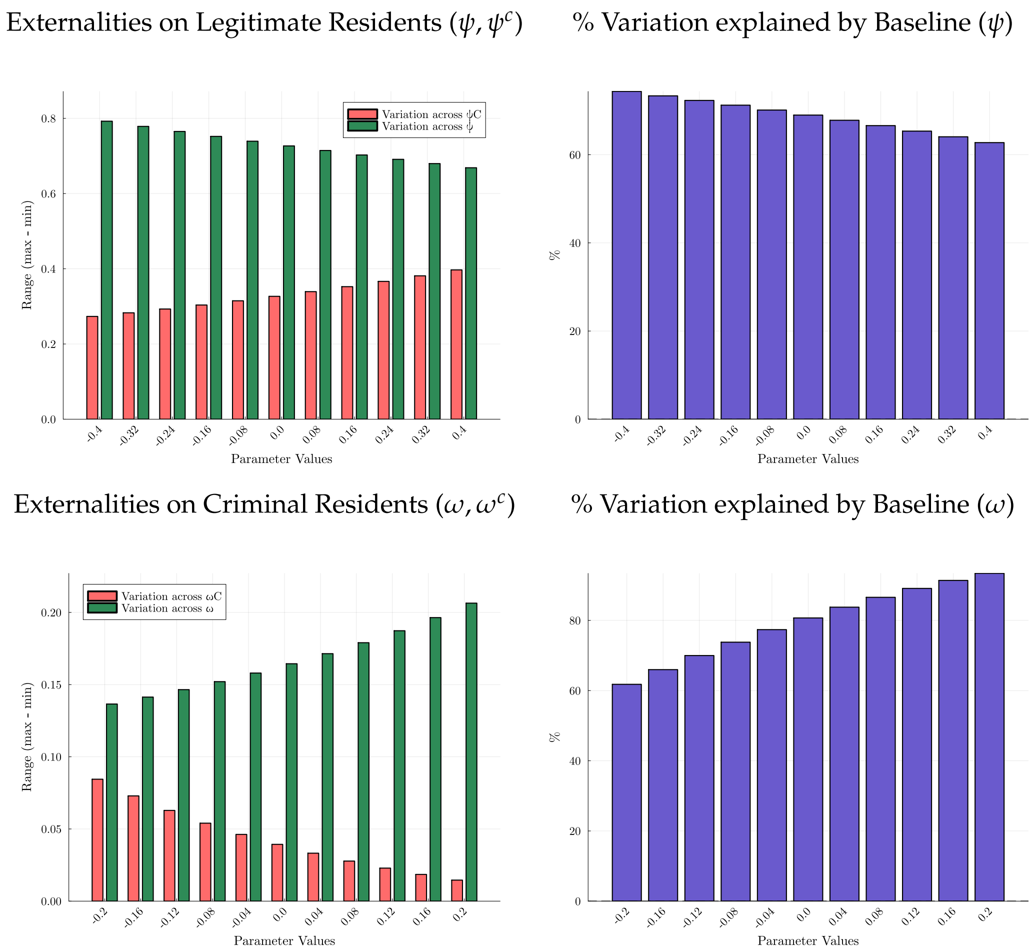
We model the crime externalities on the level of legitimate externalities. A more general modeling assumption would be to impose externalities both on the level of legitimate externalities as well as criminal externalities.

$$B_o^\ell = b_o^\ell \left(L_o^\ell\right)^{\psi^{\ell\ell}} \left(L_o^c\right)^{\psi^{c\ell}}$$
$$B_o^c = b_o^c \left(L_o^\ell\right)^{\omega^{\ell c}} \left(L_o^c\right)^{\omega^{cc}}$$

To understand the consequences of our modelling choices, we show the counterfactual effects on welfare for different combinations of $\{\psi^{\ell\ell}, \psi^{c\ell}, \omega^{\ell c}, \omega^{cc}\}$.

The results are shown in graph C.3.

Figure C.3: Range of Welfare Implications for different Amenity Externality Values



Notes: This figure shows the range of values in welfare effects of the tram for different values of crime amenities and legitimate amenities. Specifically, the x-axis shows different values of one of the parameters and the y-axis shows the range of potential welfare effects of the tram when solving the model for a range of different parameter values: $\psi^c \in (-.4, .4), \psi \in (-.4, .4), \omega^c \in (-.2, .2), \omega \in (-.2, .2)$.

We solve the model over a grid of parameter values capturing the extended amenity specification. Specifically, we consider $\psi^c \in (-0.4, 0.4)$, $\psi \in (-0.4, 0.4)$, $\omega^c \in (-0.2, 0.2)$, and $\omega \in (-0.2, 0.2)$. For each pair of externalities, (ψ, ψ^c) and (ω, ω^c), we fix one parameter on the x-axis and vary the other across its grid, obtaining the full range of welfare effects associated with changes in that parameter while keeping the other constant.

Figure C.3 presents these results. The y-axis shows the range of welfare effects in percentage points induced by each parameter, conditional on the other being fixed. We compare the baseline specification in green with the extended specification in red. The second column reports how much of the variation in welfare ranges is captured by the baseline model, computed as the share of total variation explained by the baseline specification.[45]

The main takeaway from these figures is that most of the variation in welfare effects is driven by the amenity externalities already included in the baseline version of the model. Given a fixed value for the amenity externality of criminal workers on legitimate residents, varying the amenity externalities of criminal workers and criminal residents produces only small changes in the overall range of welfare effects from improvements in transportation infrastructure. Similarly, when holding constant the amenity externality of legitimate workers and legitimate residents, changes in the amenity externality of legitimate workers on criminal residents have limited effects on the welfare impacts of transportation investments. In contrast, most of the variation arises from the baseline parameters included in the model.

C.4 SISBEN and Non-SISBEN workers

In this section, we extend the model treating SISBEN workers, which we directly observe in the data, and non-SISBEN workers, which we compute based on census counts, as different types of workers. Specifically, we denote SISBEN workers by a superscript U and Non-SISBEN workers by a superscript H.

We assume that SISBEN workers act exactly as described in the baseline version of the model and can work either in the legitimate sector or in the crime sector. On the other hand, non-SISBEN workers do not participate in the criminal sector and simply solve a residential commute decision problem given nested Frechet preferences:[46]

$$H^H(\vec{\epsilon}(x)) = \exp\left[-\sum_o \left(\sum_d (\epsilon_{od}(x))^{-\theta^H}\right)^{\frac{\eta}{\theta^H}}\right].$$

[45]Specifically,

$$\%\text{Variation} = 100 \times \frac{\text{RangeWelfare}(\psi \mid \psi^c = x)}{\text{RangeWelfare}(\psi \mid \psi^c = x) + \text{RangeWelfare}(\psi^c \mid \psi = x)}.$$

[46]This assumption is justified by the empirical observation that crime rates decline sharply with income and by definition non-SISBEN workers are part of the approximately 20% richest individuals within the city.

Origin-destination shares for non-SISBEN workers are given by:

$$\pi_{od}^{H} = \underbrace{\frac{\left(P_o^{-\beta} Q_o^{-(1-\beta)} W_o^H\right)^{\eta}}{\sum_{o'} \left(P_{o'}^{-\beta} Q_{o'}^{-(1-\beta)} W_{o'}^H\right)^{\eta}}}_{\pi_o} \underbrace{\frac{\left(w_d^H\right)^{\theta^H} \left(\tau_{od}\right)^{-\theta^H}}{\sum_{d'} \left(w_{d'}^H\right)^{\theta^H} \left(\tau_{od'}\right)^{-\theta^H}}}_{\pi_{od|o}^H}.$$

Legitimate Production. We assume that the legitimate sector production function combines SISBEN workers, non-SISBEN workers, and the fixed factor as:

$$y_d^{\ell} = A_d^{\ell} \left(L_d^{\ell}\right)^{\alpha^{\ell}} \left(F_d^{\ell}\right)^{1-\alpha^{\ell}},$$

where labor is a CES composite of SISBEN and non-SISBEN workers:

$$L_d^{\ell} = \left(\varphi^{\ell U} \left(L_d^{\ell U}\right)^{\frac{\mu-1}{\mu}} + \varphi^{\ell H} \left(L_d^{\ell H}\right)^{\frac{\mu-1}{\mu}}\right)^{\frac{\mu}{\mu-1}}$$

The elasticity of substitution across labor types is given by μ and the overall labor share α^{ℓ} and $\varphi^{\ell U} + \varphi^{\ell H} = 1$. If $\mu = 1$, then this converges to a nested Cobb-Douglas. If $\varphi^{\ell U} = 1$ the model becomes the baseline model.

The demand for workers of group g in the legitimate sector is given by:

$$L_d^{\ell g} = \left(\varphi^{\ell g}\right)^{\mu} \left(\frac{w_d^{\ell g}}{\mathcal{W}_d^{\ell}}\right)^{-\mu} L_d^{\ell} \tag{53}$$

where:

$$\mathcal{W}_d^{\ell} = \left(\sum_g \left(\varphi^{\ell g}\right)^{\mu} \left(w^{\ell g}\right)^{1-\mu}\right)^{\frac{1}{1-\mu}}$$

Defining the share of the wage bill in destination d that goes to group g, we get:

$$\phi_d^{\ell g} = \frac{\varphi^{\ell g} \left(L_d^{\ell g}\right)^{\frac{\mu-1}{\mu}}}{\left(L_d^{\ell}\right)^{\frac{\mu-1}{\mu}}}.$$

Market clearing is the same as before, with the only difference that total income by location is given by:

$$I_o \equiv v_o^U R_o^U + v_o^H R_o^H + \sum_s q_o^s F_o^s + Q_o F_o$$

where:

$$v_o^H = \sum_d \pi_{od|o}^H w_d^H$$

and:

$$v_o^U = \sum_s \sum_d \pi_{o|o}^{sU} \pi_{od|os}^{sU} w_d^{sU}$$

The inversion of wages still applies, and we can obtain:

$$\left(w_d^{\ell g}\right)^{\theta^g} = \frac{L_d^{\ell g}}{\text{FMA}_d^{\ell g}}$$

Hat Algebra. The change in labor demand is given by (Equation 53):

$$\hat{L}_d^{\ell g} = \left(\frac{\hat{w}_d^{\ell g}}{\hat{\mathcal{W}}_d^{\ell}}\right)^{-\mu} \hat{L}_d^{\ell}$$

where:

$$\hat{L}_d^{\ell} = \left(\sum_g \phi_d^{\ell g} \left(\hat{L}_d^{\ell g}\right)^{\frac{\mu-1}{\mu}}\right)^{\frac{\mu}{\mu-1}}$$

The change in the wage index is given by:

$$\hat{\mathcal{W}}_d^{\ell} = \left(\sum_g \left(\varphi^{\ell_g}\right)^{\mu} \left(\frac{w_d^{\ell_g}}{\mathcal{W}_d^{\ell}}\right)^{1-\mu} \left(\hat{w}_d^{\ell g}\right)^{1-\mu}\right)^{\frac{1}{1-\mu}}$$

which we can write as:

$$\hat{\mathcal{W}}_d^{\ell} = \left(\sum_g \phi_d^{\ell g} \left(\hat{w}_d^{\ell g}\right)^{1-\mu}\right)^{\frac{1}{1-\mu}}$$

Implementation. We solve the model in hat algebra given data on $\{w_d^{\ell g}, L_d^{\ell g}, R_o^{\ell g}\}$ for both types of workers, as well as well as values of the elasticities μ, $\alpha^{\ell g}$, and θ^g.

Thus, given data on θ^g, $\{L_d^{\ell g}, R_o^{\ell g}, L_d^c, R_o^c\}$, as well as values of the elasticity μ, we can solve the model, plus the rest of the baseline parameters of the model.

We obtain labor and resident counts from Pila, the census and the SISBEN from which we can observe both all of the legitimate workers at destination that we can match to the SISBEN and treat the rest as non-SISBEN workers. We use the following parameters from Tsivanidis (2023) who calibrates high-skill and low-skill parameters for Bogota.

Table C.3: Parameterization

	Parameter	Value	Source
Commute Elasticity High Skill	θ^H	2.655	Tsivanidis (2023)
Commute Elasticity Low Skill	θ^U	3.8	Estimated
Elasticity of Substitution High-Skill/Low-Skill	μ	1.42	Card (2009)

Table C.4: Effects of Cable Line P and Tram with Sisben and Non-Sisben workers

	%Δ Share Legitimate (avg.)	%Δ Share Crime Origin (avg.)	%Δ Welfare	%Δ Welfare Non Sisben
Tram				
Baseline	0.0033	-0.0452	0.1852	–
SISBEN, Non-SISBEN	0.0038	-0.062	0.2023	0.1466
Cable P				
Baseline	0.0227	-1.0027	1.5206	–
SISBEN, Non-SISBEN	0.0255	-1.2275	1.6993	1.0236

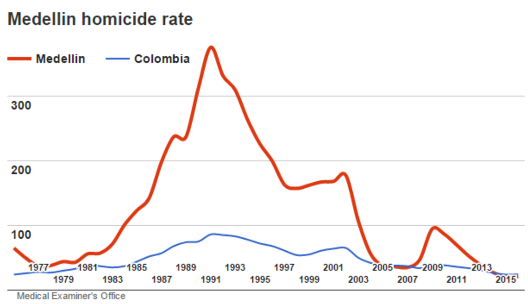
Notes: This table shows the counterfactual effects of Cable P and the Tram Line both in the baseline Both in the baseline version of the model as well as in the extended version of the model which treats SISBEN and non-SISBEN workers as different types of workers. The first panel shows the effects of the Tram, while the second panel shows the effects of Cable P.

Results. Table C.4 compares the counterfactual effects of the tram as well as line P in the baseline version of the model and in the model extension that treats SISBEN and non-SISBEN as different types of workers. Results indicate that aggregate variables in the extended version of the model behave similarly to the baseline version of the model. Importantly, welfare effects are similar as well: the welfare effects for SISBEN workers are somewhat larger relative to the baseline version of the model but of similar magnitude. Importantly, but non-SISBEN workers also benefit from the transportation investments due to the fact that decreases in criminal activity, reduce negative externalities across the city as a whole, which benefits all residents.

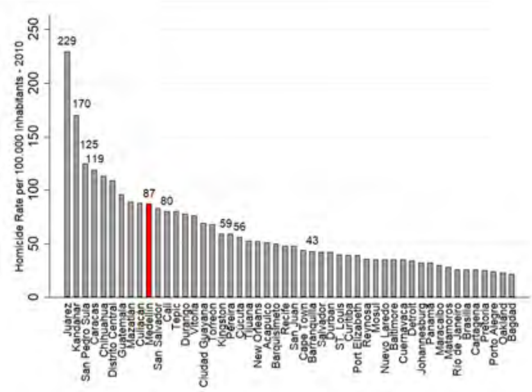
D Additional Figures and Tables

Figure D.1: Homicide Rates in Medellín Over Time, and Relative to Other Cities

(a) Homicide Rates in Medellín, 1997-2015

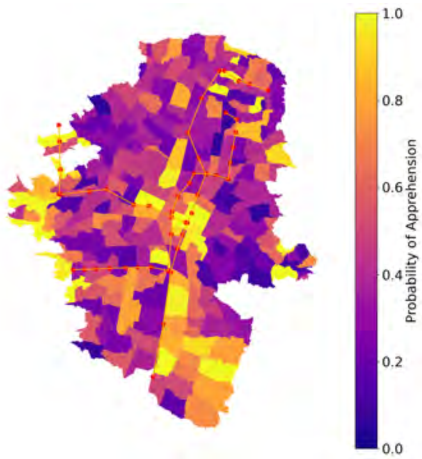


(b) Highest Homicide-rate Cities, 2010



Note: Homicides rates in Medellín over time (left panel), shows the number of recorded homicides per 100,000 individuals in Medellín (red line) and the average for Colombia (blue line). Data from the *Consejo Ciudadano para la Seguridad Public y la Justicia Penal*. The right panel shows the average homicide rates in 2010 in cities across the world, where Medellín is represented in red.

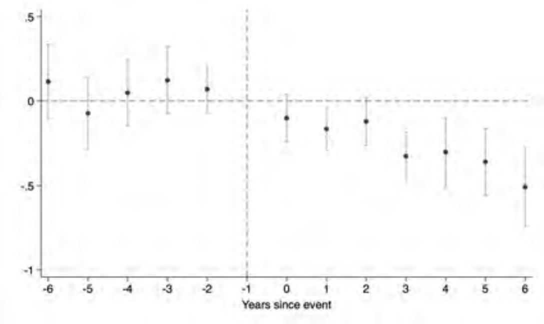
Figure D.2: Average Homicide Arrest Rate by Destination: p_d



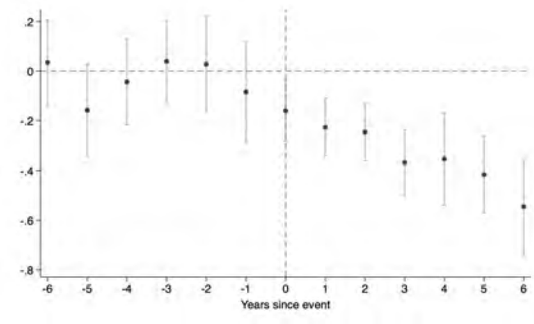
Notes: This map shows the average arrest rate $\#\text{arrests}_d/\#\text{homicides}_d$ across the sample.

Figure D.3: Robustness in methods for Event Study estimation

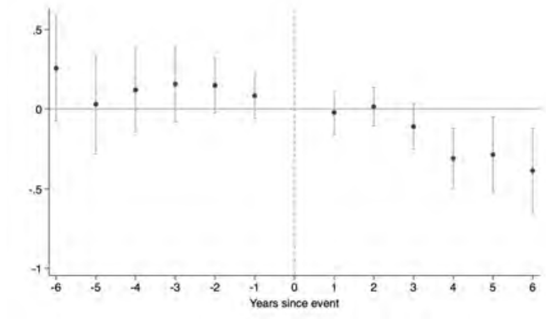
(a) Crime origin (baseline)



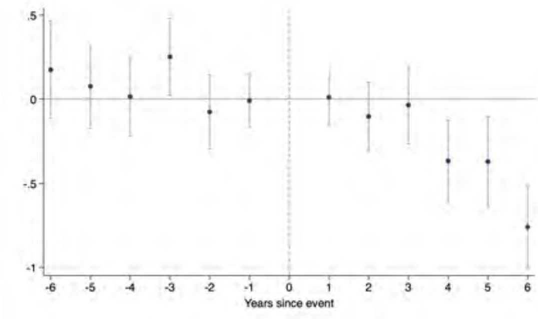
(b) Crime origin (Borusyak and Hull, 2023)



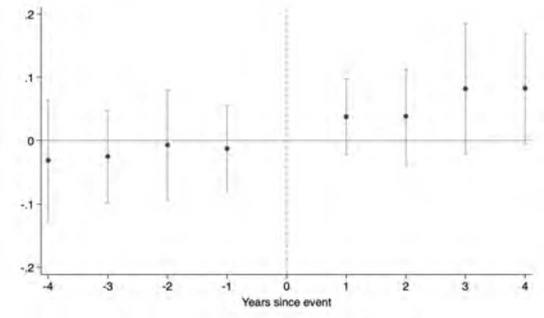
(c) Crime origin (Sun and Abraham, 2021)



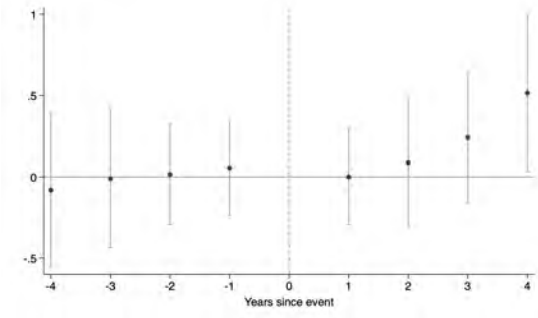
(d) Crime destin. (Sun and Abraham, 2021)



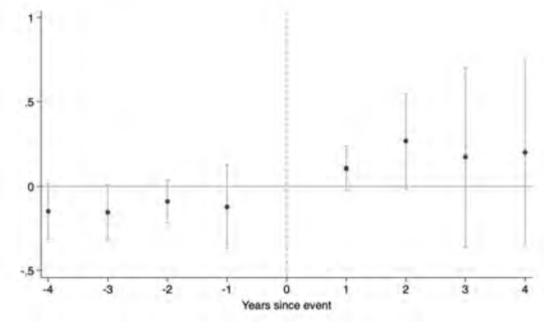
(e) Emp. origin (Sun and Abraham, 2021)



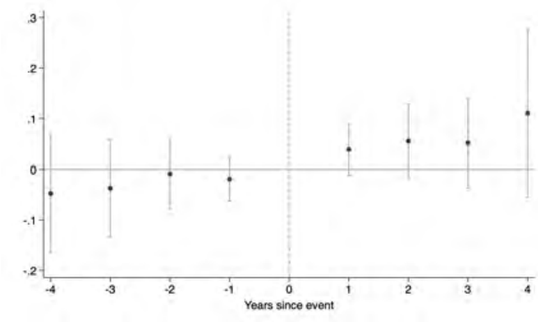
(f) Wages origin (Sun and Abraham, 2021)



(g) Wages destin. (Sun and Abraham, 2021)



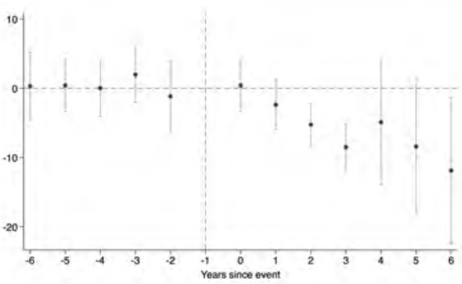
(h) Log Rent (Sun and Abraham, 2021)



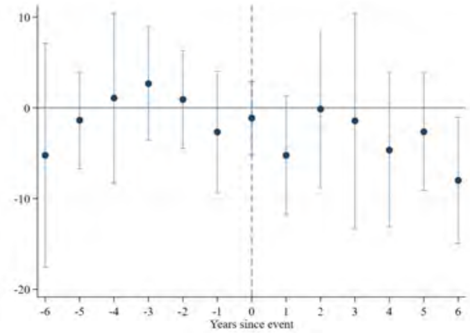
Notes: Figure shows the effect of a new transport building on crime, employment, rents, and wage outcomes. The crime database at origin and destination goes from 2002 to 2015. The employment at origin is from 2004 to 2016, and the rent data is from 2005 to 2018. The employment at destination and wages database goes from 2007 to 2017.

Figure D.4: Effects of new transit lines on Crime and Employment measured in levels

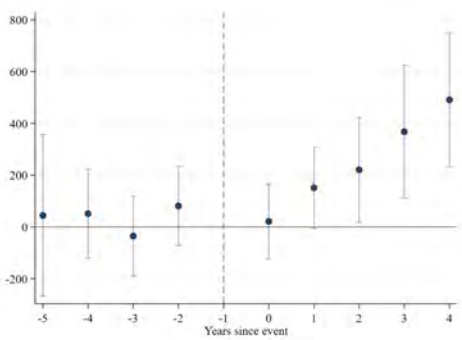
(a) Crime at origin



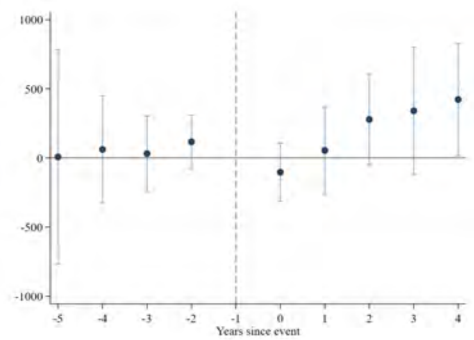
(b) Crime at destination



(c) Employment at origin

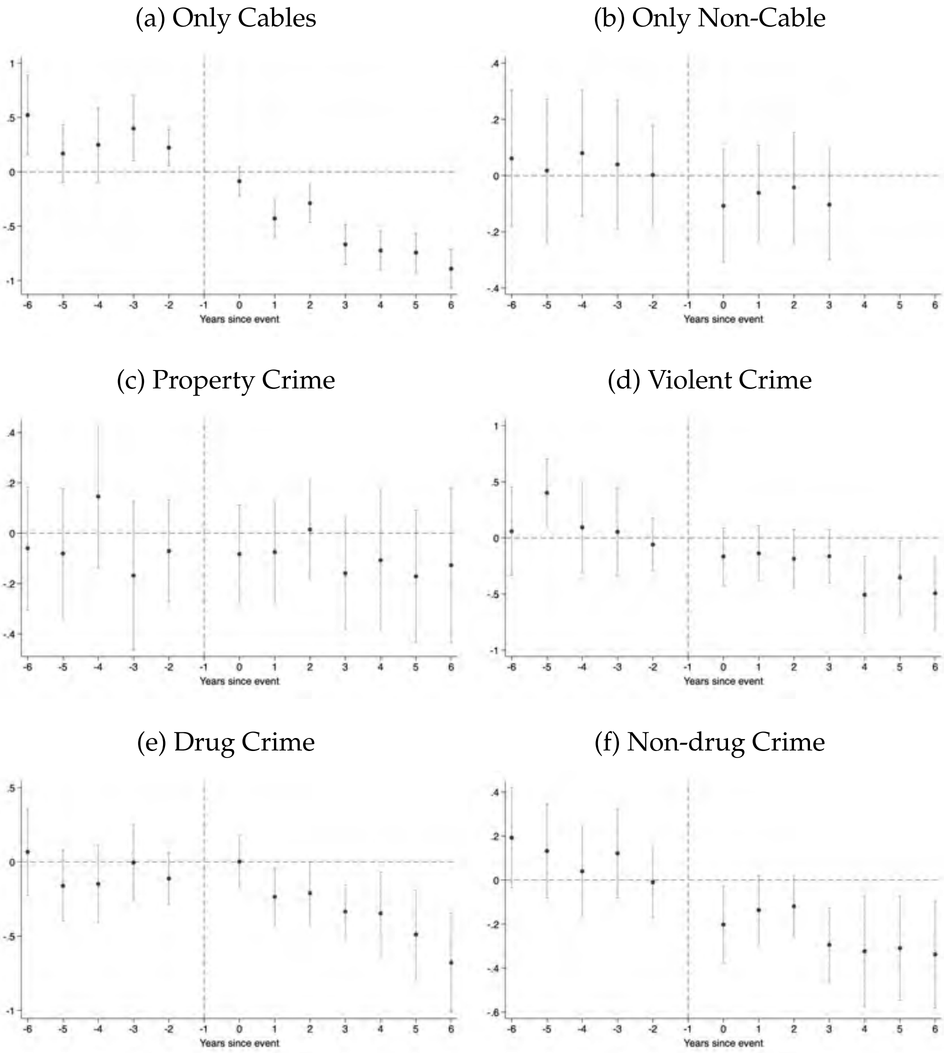


(d) Employment at destination



Notes: Figure shows the effect of a new transport building on crime, employment, rents, and wage outcomes. We use new transport buildings: Cable K started operations in 2004, Cable J started operations in 2008, Rapid Bus Transport started operations in 2012, and Tram started operations in 2015. The crime database at origin and destination goes from 2002 to 2015. The employment at origin database spans 2004 to 2016. The employment at destination goes from 2007 to 2017.

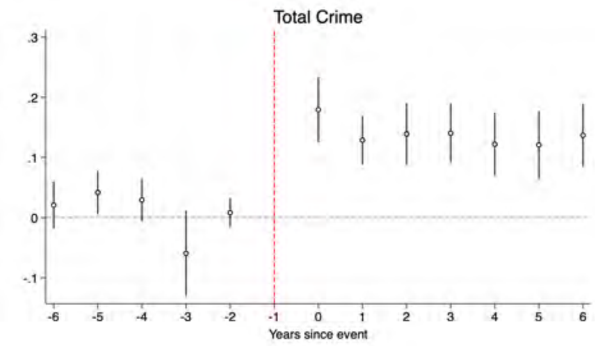
Figure D.5: Event Studies of 'crimes at origin' by type of transportation, and crime



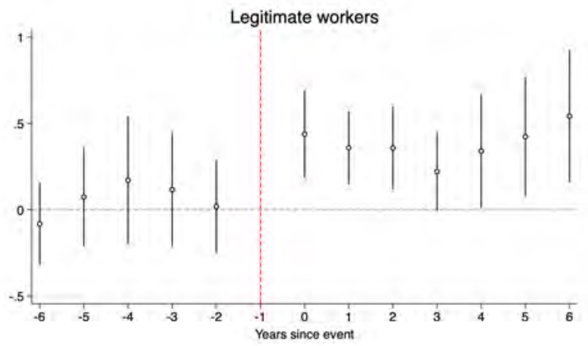
Notes: Figure shows the effect of a new transit lines on crime. The top panels compare impacts driven by cables, vs non-cables (BRT and tram). Cable K started operations in 2004, Cable J started operations in 2008, Rapid Bus Transport started operations in 2012, and Tram started operations in 2015. The crime database at origin and destination goes from 2002 to 2015.

Figure D.6: Origin-Destination Gravity Event Studies

(a) Crime flows



(b) Legitimate workers flows



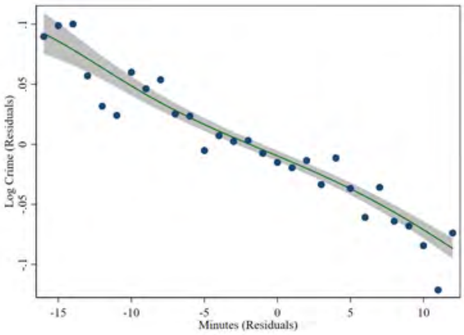
Notes: We estimate the following event study specifications (in PPML):

$$Crime_{odt} = exp\left(\alpha_{od} + \alpha_{ot} + \alpha_{dt} + \sum_{\underline{C}\leq k\leq\overline{C}} \beta_k Treatment_{od,t-k} + \gamma\left(Post_{odt} \times Distance_{od}\right)\right)\epsilon_{odt},$$

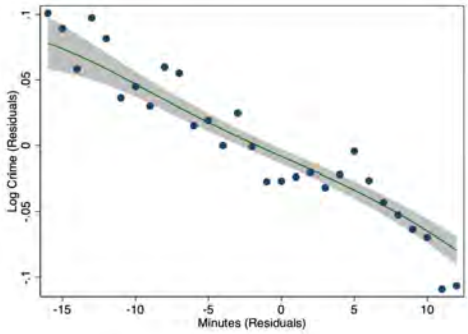
where α_{od} indicates an origin-destination comuna fixed effect, α_{ot} indicates an origin-time fixed effect, α_{dt} indicates a destination-time fixed effect, $Treatment_{od,t-k}$ is an indicator of an origin-destination pair that experienced a percentage commute change above the percentile 75 at year $t-k$. We also add as control the interaction of a post-intervention dummy and the baseline distance between origin and distance pair $Post_{odt} \times Distance_{od}$. This interaction allows us to control for any potential distance effect before and after a new transport building. Therefore, we can interpret β_k as the effect of a change in the commute time due to a new transport building on the commute flows at time k, holding constant distances. Given the presence of zero flows, we estimate it using Poisson Pseudo Maximum Likelihood (PPML). The figure shows the effect of a new transport building (Cable K, J, BRT, and Tram) on crime and legitimate workers' flows. Treatment is defined as an Origin-Destination pair that experiences a change in commute above the percentile 75 within each event. The crime flow data spans 2002 to 2015. The legitimate workers' flow data is from 2007 to 2017. Standard errors are clustered at origin-by-destination level.

Figure D.7: Semi-Parametric Residualized Gravity Relationship

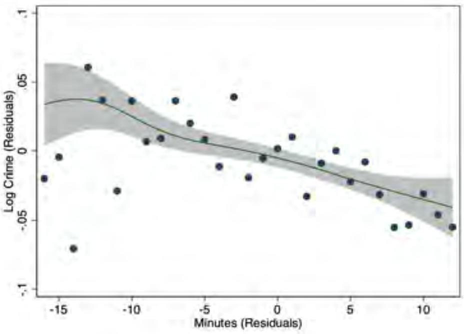
(a) Any crime



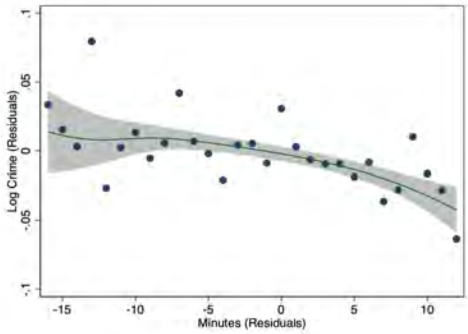
(b) Drugs



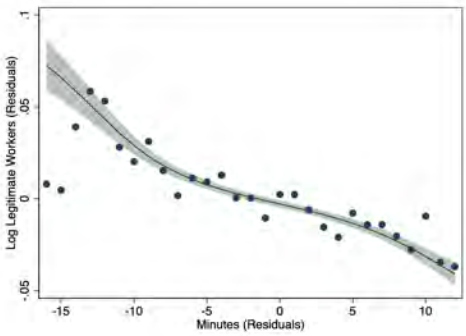
(c) Violent



(d) Property

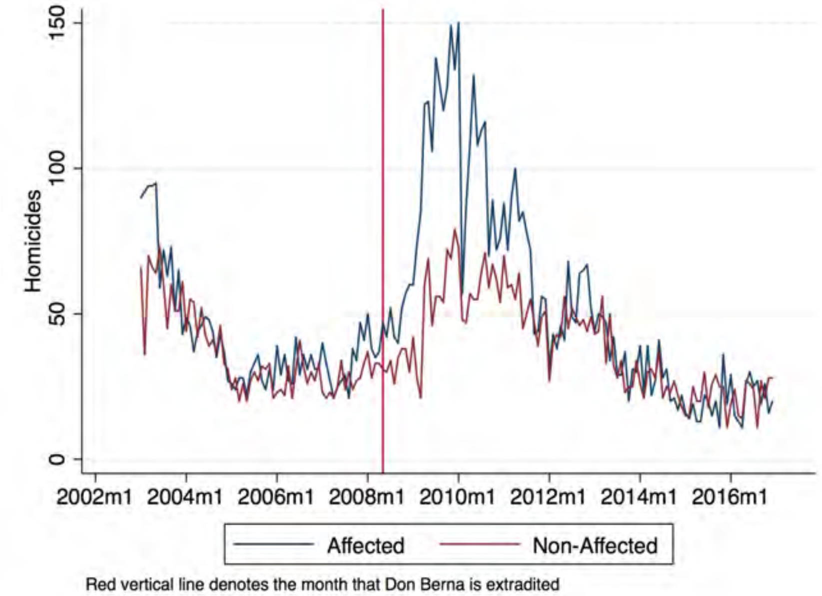


(e) Formal-workers



Notes: Figure shows the local polynomial regression between the residualized crime flows, formal-workers flows, and commuted time. Residuals obtained after controlling for destination-by-time FE, origin-by-time FE, and origin-by-destination comuna FE. The crime flow data spans 2002 to 2015.

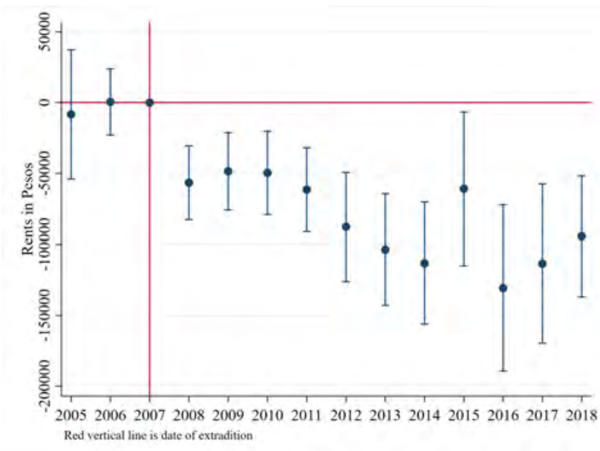
Figure D.8: Change in Homicides After the Extradition of Crime Lord, Don Berna



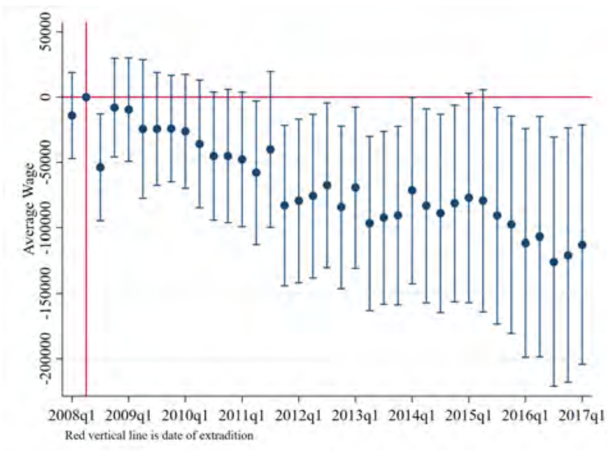
Notes: This graph shows the homicide rate by neighborhoods that Don Berna used to be in charge of (affected), and all other neighborhoods (not affected). After his extradition, there was a spike in crime in his neighborhoods.

Figure D.9: Effect of Don Berna Shock

(a) Rents

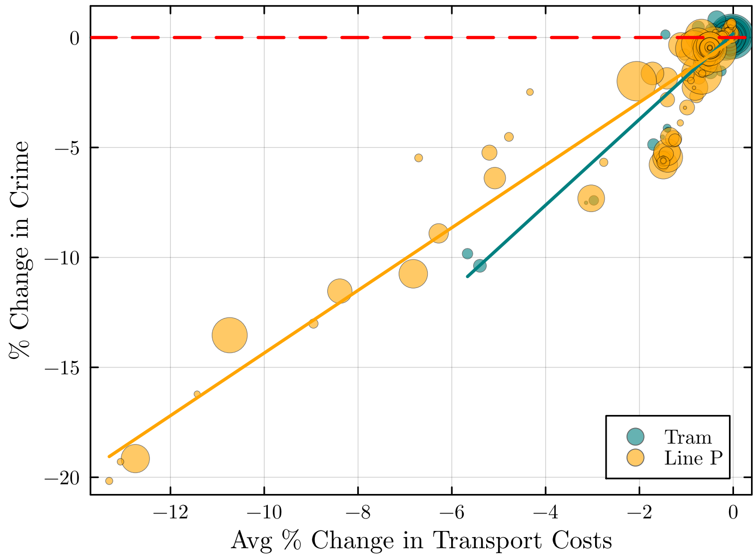


(b) Wage



Notes: Figures show the effect of Don Berna's extradition on those neighborhoods that Don Berna used to be in charge of. The left panel shows property rental rates. The right panel shows quarterly wages for formal sector workers.

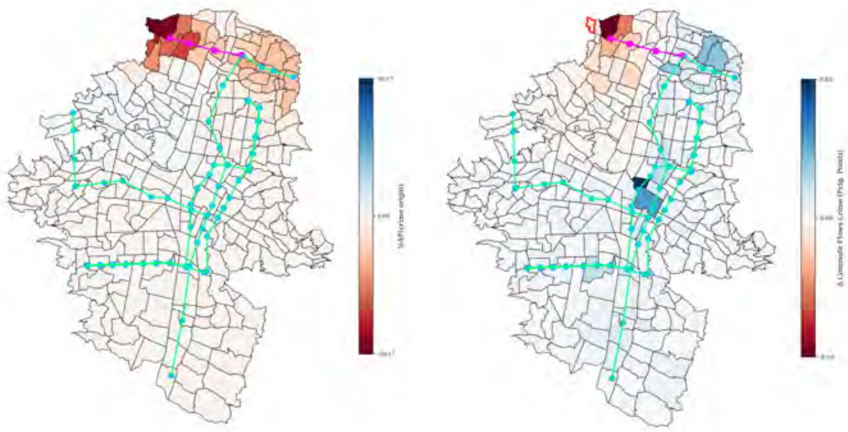
Figure D.10: Change in Crime by Change in Commute Times



Notes: This graph shows the changes in transportation costs (x-axis) and the model-predicted change in crime rates (y-axis) for the neighborhoods affected by Line P and the tram.

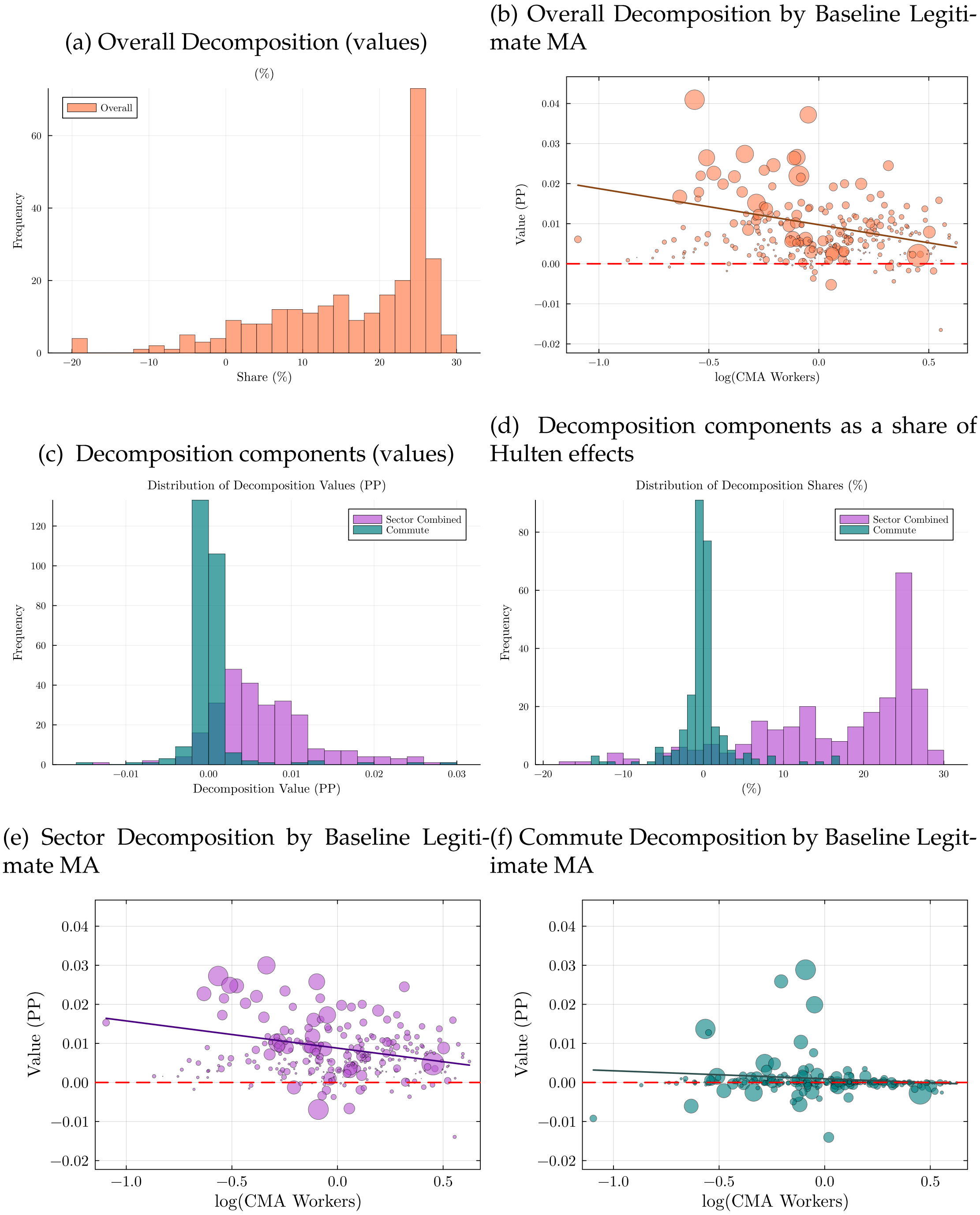
Figure D.11: Change in crime rate: North-west Cable line

(a) Prob(Criminal) at Origin (b) Crime Rate at Destinations



Notes: Left-panel map shows the model implied percent change in the probability of becoming a criminal conditional on origin, $\pi^c_{o|o}$ across neighborhoods of origin, given the change in commute costs. The right-panel map shows the model-implied percent change in the probability of committing a crime conditional on origin, $\pi^c_{od|o}$ across destinations, given the change in commute costs.

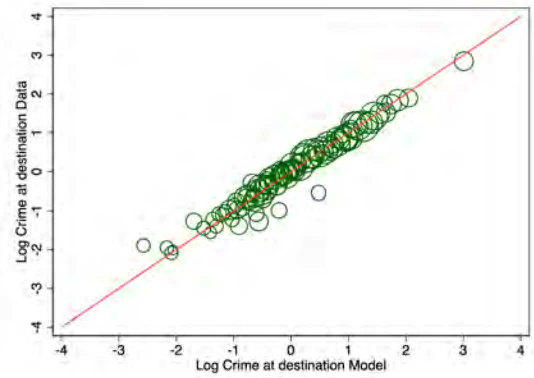
Figure D.12: Reducing Commute Costs by Each Neighborhood



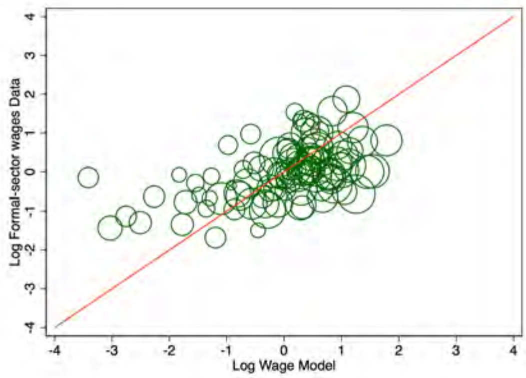
Notes: Scatter plots show the relationship between changes in city-level decomposition outcomes against the baseline legitimate-sector market access for the treated origin o, where treatment is a ten percent reduction in commute costs ($\tau'_{od} = 0.9\tau_{od} \ \forall \ d$). That is, each point x-axis is the legitimate-sector CMA of the neighborhood that receives the transport subsidy. Histograms show the citywide effects induced by a 10% reduction in commute costs on outcomes related to the criminal externalities decomposition.

Figure D.13: Data validation of the model

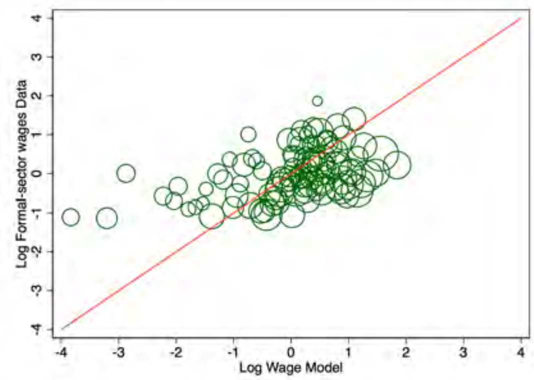
(a) Criminals



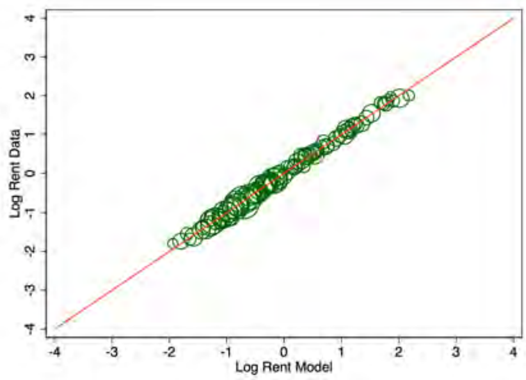
(b) Formal-sector Wages



(c) Income (Informal+Formal)



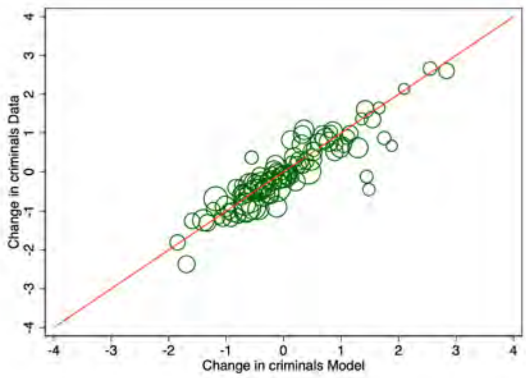
(d) Property Rental Rates



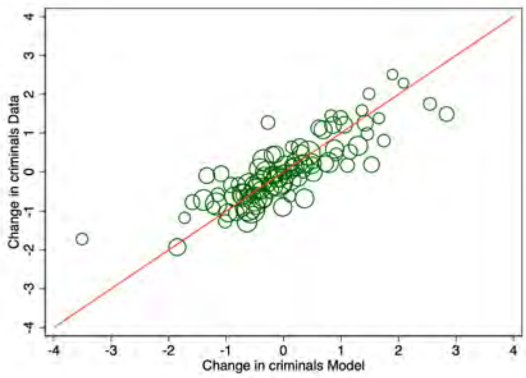
Notes: Scatter plots show the correlation between the model prediction on the Criminals, Wages, and Rents with actual data from 2007 to 2016. As sources for the actual data, we use the Police records from 2007 to 2016, the Encuesta de Calidad de Vida (ECV) for the household income and rents from 2007 to 2016, and the PILA for the formal-sector wages from 2007 to 2016. Panel a shows the correlation between the predicted number of criminals for the model and the actual crime rate in the data. Panel b shows the correlation between the predicted wage for the model and the actual formal-sector wage. Panel c shows the correlation between the model-predicted earnings and the actual household income. Panel d shows the correlation between predicted rents for the model and the actual rents. We show binned scatter plots using 100 bins with the same number of neighborhoods in each bin.

Figure D.14: Change in criminals predicted by model using Cable J, Bus Rapid Transit, and Tram counterfactual against actual change in criminals from actual data

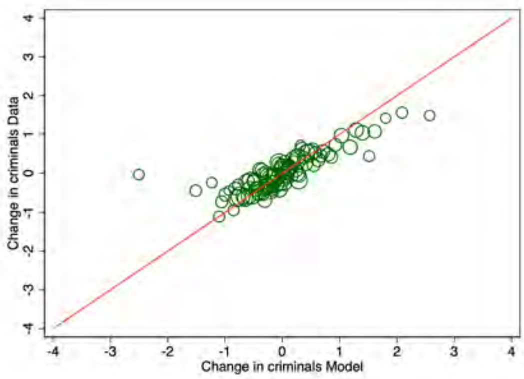
(a) Cable J



(b) Bus Rapid Transit



(c) Tram



Notes: Scatter plots show the correlation between the model prediction and raw data for the change of criminals; as a result of the new commute time after opening of the Cable J, Bus Rapid Transit, and Tram. As sources for the actual data, we use the Police records. Panel a shows the correlation between the predicted change in criminals for the model and the actual change in criminals in the data after Cable J's opening. Panel b shows the correlation between the predicted change in criminals for the model and the actual change in criminals in the data after the Bus Rapid Transit opening. Panel c shows the correlation between the predicted change in criminals for the model and the actual change after the Tram opening. We show binned scatter plots using 100 bins with the same number of neighborhoods in each bin.

Table D.1: The Impact of New Stations: Robustness Checks (without BRT)

	Log Crime Origin	Log Crime destination	Log Employment Origin	Log Employment destination	Log Wages Origin	Log Wages destination	Log Rents
			Panel A: All non-BRT stations				
Post × Station	-0.547***	-0.349**	0.410***	0.480	0.286***	0.683	0.066**
	(0.060)	(0.133)	(0.085)	(0.063)	(0.089)	(0.768)	(0.030)
Observations	1,036	994	1,027	935	1,027	935	1,190
Mean	49.6	70.345	3009.005	6507.946	13.148	14.051	12.689
Years data	2002-2015	2002-2015	2004-2016	2007-2017	2004-2016	2007-2017	2005-2018
			Panel B: Dropping nodal station				
Post × Station	-0.487***	-0.274**	0.414***	0.487***	0.262**	0.672	0.057*
	(0.067)	(0.140)	(0.085)	(0.062)	(0.090)	(0.760)	(0.030)
Observations	1,008	966	1,014	924	1,014	924	1,176
Mean	51	76.423	3009.005	6507.946	13.167	14.051	12.689
Years data	2002-2015	2002-2015	2004-2016	2007-2017	2004-2016	2007-2017	2005-2018
			Panel C: Instrumental variables (Cables only)				
Post × Station	-0.605**	-0.889	0.169***	0.643	0.115	0.539	0.275***
	(0.165)	(0.683)	(0.044)	(1.641)	(0.078)	(0.428)	(0.059)
Observations	888	852	912	666	912	666	666
Mean	27.922	54.102	2270.186	2518.503	0.505	0.632	0.196
F-stats	63.34	62.36	63.02	762.65	63.02	762.65	762.65
Years data	2004-2015	2004-2015	2004-2015	2007-2015	2004-2015	2007-2015	2007-2015

Note: Tables show robustness to using non-BRT transit changes, dropping nodal stations, and an instrumental variables strategy. In panel A and B we use as treatments Cable K, J and Tram lines. In panel C we use as treatment Cable K and J lines. The crime database at origin and destination spans 2002 to 2015. The employment at origin is from 2004 to 2016, and rent data from 2005 to 2018. The employment at destination and wages database goes from 2007 to 2017. Mean of dependent variables is reported in levels. Wages are measured in millions of pesos. All specifications include year and neighborhood fixed effects and standard errors clustered at the neighborhood level.

Table D.2: Neighborhood Slope Predicting New Cable Lines

	(1)	(2)
	New Line (0/1)	
Candidate Line Slope	0.496***	0.347***
	(0.0623)	(0.0126)
Observations	888	666
R-squared	0.917	0.962
F-stat	63.336	762.650
Range	2004-2015	2007-2015

Note: Each observation is a candidate line. We calculate candidate lines for Cables K and J, which provides different sets of candidate lines from prior to 2008 and post-2008. The outcome variable is an indicator for whether a potential line was actually built. The explanatory variable "Candidate Line Slope" is the average of the slopes of the candidate lines passing through that neighborhood. The slope of each candidate line is the difference in altitude between the start and end points divided by the length of the line. Both specifications include year and neighborhood fixed effects and standard errors clustered at the neighborhood level. The F-stat represents the strength of an instrumental variables specification when this regression is used as a first stage.

Table D.3: Robustness Effect of Travel Time From Origins to Destination between Neighborhoods with Gang Boundaries

	Any crimes		Violent Crime		Legitimate Work	
	(1)	(2)	(3)	(4)	(5)	(6)
Minutes from O-D	-0.0676***	-0.0674***	-0.0644***	-0.0641***	-0.0386***	-0.0382***
	(0.0034)	(0.00345)	(0.0064)	(0.00642)	(0.0078)	(0.00775)
Minutes from O-D*		-0.00469*		-0.00691		-0.0578
O-D in different gang territory		(0.00264)		(0.00509)		(0.0651)
Observations	1,013,054	1,013,054	1,013,054	1,013,054	217,083	217,083
Destination-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination-by-Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
SE Cluster			Origin and Destination			

Notes: Tables show the effect of changes in travel time between origin-destination pairs on the resulting flows in crime and legitimate-sector workers between these neighborhoods. We estimate this standard gravity equation using pseudo maximum likelihood (PPML) with high-dimensional fixed effects, and cluster our errors at the origin and destination level. Columns 1, 3, and 5 show the coefficients of Table 2. Columns 2, 4, and 6 show the coefficients of the main effect of travel time and the interaction with an indicator for commutes lying between two neighborhoods traversing gang boundaries. We thank Arantxa Rodriguez-Uribe for sharing data on gang boundaries.

Table D.4: Commuting Elasticity by Type of Crime

	Any crimes	Violent Crime	Property	Drugs	LACE Crimes	Domestic Crimes	Local Crimes
Minutes from O-D	-0.0676***	-0.0644***	-0.0645***	-0.0682***	-0.0675***	-0.00112	0.00585
	(0.0034)	(0.0064)	(0.0052)	(0.0036)	(0.0062)	(0.00079)	(0.00678)
Observations	1,013,054	1,013,054	1,013,054	1,013,054	1,013,054	1,013,054	1,013,054
Dest-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dest-by-Origin FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Cluster				Origin and Destination			

Notes: Tables show the effect of changes in travel time between origin-destination pairs on the resulting flows in crime between these neighborhoods by type of crimes. LACE crimes are those "likely associated with criminal enterprises". Local crimes have the lowest (below percentile 25) average commute time between origin and destination of crime before 2004. We estimate this standard gravity equation using pseudo maximum likelihood (PPML) with high-dimensional fixed effects, and cluster our errors at the origin and destination level.

Table D.5: Individual-Level Regressions on Sorting vs Sector Choice: Sample of individuals who lived in treated or control neighborhoods

	Crime (1/0)				
	All	Movers	Mover In	Mover Out	Stayers
Post $\times$ Station	-0.0004***	-0.00014	0.00056	0.0007	-0.0006***
	(0.00015)	(0.0002)	(0.0006)	(0.0004)	(0.0002)
Observations	6,784,316	2,263,660	340,830	397,880	4,520,656
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Mean	0.0101	0.0054	0.0062	0.0056	0.0121
Mean Control	0.0099	0.0048	0.0066	0.0055	0.0120

Notes: The table shows the Diff-in-Diff estimates of the effect of new transit lines on the probability of arrests at the individual level. The sample consists of individuals who lived at least one year in a treated or control neighborhood from 2002 to 2015. Neighborhoods around 1 km from a new transport building are treated. Neighborhoods between 1km and 2 km from a new transport building are controls.

Table D.6: Robustness: Market Access Structural Equations Estimation

	$Log(Crime_d)$	$Log(LegitimateWorkers_d)$	$Log(Wages_d)$	$Log(Crime_o)$	$Log(LegitimateWorkers_o)$	$Log(Wages_o)$	$Log(Rents_o)$
				Panel A: OLS			
$Log(FMA^c)$	0.656***	-2.672***	-0.440***	-1.779***	-0.241	-0.752***	-1.054***
	(0.216)	(0.744)	(0.129)	(0.663)	(0.540)	(0.231)	(0.269)
$Log(FMA^\ell)$		5.635***	0.731***	4.169**	2.812**	2.188***	2.173***
		(1.182)	(0.187)	(1.991)	(1.410)	(0.621)	(0.765)
$Log(CMA^c)$				-1.815	-1.074	0.00992	0.318
				(1.324)	(0.871)	(0.282)	(0.242)
$Log(CMA^\ell)$				1.025	-0.402	-0.828	-0.715
				(2.250)	(1.644)	(0.503)	(0.571)
			Panel B: Donaldson and Hornbeck (2016b)				
$Log(FMA^c)$	0.943***	-0.584	-0.378***	4.745***	2.045***	-0.974***	-1.320***
	(0.216)	(0.750)	(0.134)	(0.694)	(0.535)	(0.178)	(0.160)
$Log(FMA^\ell)$		2.919***	0.680***	-8.402***	-3.505***	1.952***	2.255***
		(1.116)	(0.194)	(1.821)	(1.259)	(0.490)	(0.552)
$Log(CMA^c)$				1.860***	0.223	-0.604***	-0.149
				(0.703)	(0.516)	(0.179)	(0.170)
$Log(CMA^\ell)$				-0.889	0.426	0.702*	0.437
				(1.363)	(0.923) (0.405)	(0.523)	
Observations	538	538	525	410	538	490	538

Notes: Panel A show neighborhood outcomes as functions of Firm and Commuter market access for 2007 and 2010. Panel B show the neighborhood outcomes as functions of Firm and Commuter market access for years 2007 and 2010 following the Donaldson and Hornbeck (2016b) method of estimation, where we only leverage changes in commute times that occur outside a 1.5km radius. Outcomes used in regressions come from the rescaled data. In all specifications, we control for communa and year fixed effects. Standard errors clustered at the neighborhood level are reported in parentheses.

Table D.7: Data validation of the model using Tram, BRT, and Cable J counterfactual

	Data			
	Change in criminals	Change in Formal Wage	Change in Income	Change in Rental rates
	Panel A: Cable J			
Model	0.912***	0.834**	0.314**	0.653***
	(0.0558)	(0.375)	(0.120)	(0.214)
Observations	538	538	538	538
R-squared	0.641	0.078	0.461	0.968
	Panel B: BRT			
Model	0.725***	0.425**	0.249*	0.610*
	(0.0803)	(0.174)	(0.120)	(0.344)
Observations	807	807	807	807
R-squared	0.462	0.465	0.886	0.006
	Panel C: Tram			
Model	0.687***	0.722**	0.152*	0.450***
	(0.0726)	(0.285)	(0.0831)	(0.0341)
Observations	807	807	807	807
R-squared	0.545	0.154	0.258	0.304

Notes: Table shows the regression of the year-on-year change in the Number of criminals, Formal-workers' wages, Legitimate-workers' wages, and Rental rates observed in the actual data against the predicted change by the model in 3 counterfactual: Tram, Bus Rapid Transit (BRT), and Cable J. As sources for the actual data, we use the Police records, the Encuesta de Calidad de Vida (ECV) for the household income and rental rates, and PILA for the formal-sector wages in years 2007-2012 (Cable J), 2010-2015 (BRT), and 2012-2016 (Tram). Regressions include neighborhood and year fixed effects. Standard errors in parentheses clustered at the neighborhood level.

Table D.8: Market access as predictor of Outcomes of study from Actual Data and Model Data

	$Log(Crime_d)$		$Log(Legitimate_d)$		$Log(Wage_d)$		$Log(Crime_o)$		$Log(Legitimate_o)$		$Log(Rent)$	
Panel A: Actual data												
$Log(FMA^c)$	0.656***	0.744***	-2.672***	-3.050***	-0.475***	-0.593***	-0.903	-1.769**	-0.241	-0.398	-1.054***	-1.493***
	(0.216)	(0.212)	(0.744)	(0.804)	(0.163)	(0.175)	(0.665)	(0.876)	(0.540)	(0.679)	(0.269)	(0.315)
$Log(FMA^\ell)$			5.635***	6.192***	0.688***	0.882***	0.675	2.564	2.812**	3.023*	2.173***	3.339***
			(1.182)	(1.264)	(0.264)	(0.283)	(1.819)	(2.439)	(1.410)	(1.747)	(0.765)	(0.929)
$Log(CMA^c)$							0.427	0.866	-1.074	-1.152	0.318	0.144
							(0.974)	(1.007)	(0.871)	(1.042)	(0.242)	(0.315)
$Log(CMA^\ell)$							-0.532	-2.036	-0.402	-0.280	-0.715	-0.919
							(2.127)	(2.132)	(1.644)	(2.049)	(0.571)	(0.698)
Panel B: Model data												
$Log(FMA^c)$	0.537**	0.565**	-2.641***	-3.092***	-0.689***	-0.806***	-1.152*	-2.167**	-0.239	-0.544	-1.211***	-1.577***
	(0.233)	(0.231)	(0.723)	(0.809)	(0.186)	(0.208)	(0.698)	(0.931)	(0.540)	(0.680)	(0.271)	(0.323)
$Log(FMA^\ell)$			5.561***	6.232***	1.198***	1.373***	1.551	4.407*	2.719*	3.635**	2.608***	3.572***
			(1.144)	(1.267)	(0.294)	(0.326)	(1.899)	(2.564)	(1.420)	(1.755)	(0.795)	(0.958)
$Log(CMA^c)$							0.683	1.189	-1.089	-1.047	0.219	0.135
							(0.986)	(1.121)	(0.870)	(1.049)	(0.259)	(0.330)
$Log(CMA^\ell)$							-1.362	-3.559	-0.290	-0.796	-0.687	-0.942
							(2.128)	(2.438)	(1.651)	(2.090)	(0.613)	(0.731)
Observations	538	538	538	538	538	538	538	538	538	538	538	538
Method	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
F-stat		38209.720		1810.568		241.005		241.005		241.005		241.005

Notes: Panel (a) shows the linear regressions between outcomes from the actual data and market access variables. Panel (b) shows the linear regressions between outcomes from the model data and market access variables. The sample is at the neighborhood-year level for the years 2007 and 2011. Actual crime origin comes from a match between the police records and Sisben. Actual crime destination comes from police records. Actual legitimate workers' origin and Rents come from Encuesta de Calidad de Vida. Actual legitimate workers' destination and wages come from PILA. Outcomes are rescaled as indicated in Appendix A.2. Model outcomes result from solving the model with the parameter estimated and the actual commute times for years 2007 and 2011. For the IV method, we use the market access terms as instruments, holding fixed the initial number of residents and workers by sector. In all specifications, we control for communa and year fixed effects.

Table D.9: Effect of a New Station on the Probability of Arrest

	Probability of Arrest (Arrests per Report)		
	Property-Homicides	Homicides	Property
Post $\times$ Stations	0.0363	-0.00347	0.108
	(0.0320)	(0.0351)	(0.0683)
Observations	3,497	3,497	3,497
Neighborhood Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
R-squared	0.229	0.249	0.224

Notes: The first two columns of Panel A show difference-in-differences estimates for being close to a station, and the probability of arrest. Column 1 shows the effect on the combined probability of arrest for property crimes and homicides. Columns 2 and 3 show the effect on the probability of arrest of homicides and property crimes, respectively.

E Estimation

In this appendix, we show the derivations of estimation Equations 13, 14, and 15. We also discuss how we calculate our shift-share instrument.

E.1 Sectoral Labor Supply Elasticity κ, Endogenous Residential Amenities ψ, ω

We now start from the relative labor supply equation:

$$\frac{R^{\ell}_{ot}}{R^{c}_{ot}} = \left(\frac{B^{\ell}_{ot}}{B^{c}_{ot}}\right)\left(\frac{W^{\ell}_{ot}}{W^{c}_{ot}}\right)^{\kappa}$$

Taking logs on both sides, we get:

$$\log\left(\frac{R^{\ell}_{ot}}{R^{c}_{ot}}\right) = \log\left(\frac{B^{\ell}_{ot}}{B^{c}_{ot}}\right) + \kappa\log\left(\frac{W^{\ell}_{ot}}{W^{c}_{ot}}\right)$$

We assume a specification of externalities:

$$\left(\frac{B^{\ell}_{ot}}{B^{c}_{ot}}\right) = \left(\frac{b^{\ell}_{ot}}{b^{c}_{ot}}\right)\left(L^{\ell}_{ot}\right)^{\psi}\left(L^{c}_{ot}\right)^{\omega}$$

where the subscript d indicates that these are legitimate and criminal sector workers measured at the destination level for that neighborhood (i.e., the number of workers that end up in that neighborhood) and the subscript o is the origin-relevant measure for that neighborhood (e.g., the number of residents).

Substituting this specification into the relative labor supply equation yields:

$$\log\left(\frac{R^{\ell}_{ot}}{R^{c}_{ot}}\right) = \psi\log L^{\ell}_{ot} + \omega\log L^{c}_{ot} + \kappa\left[\frac{1}{\theta^{\ell}}\log\left(CMA^{\ell}_{ot}\right) - \frac{1}{\theta^{c}}\log\left(CMA^{c}_{ot}\right)\right] + \log\left(\frac{b^{\ell}_{ot}}{b^{c}_{ot}}\right)$$

Rewriting the unobserved portion of the amenities as an error term and adding a term for controls, we get:

$$\log\left(\frac{R^{\ell}_{ot}}{R^{c}_{ot}}\right) = \alpha_o + \alpha_t + \psi\log L^{\ell}_{ot} + \omega\log L^{c}_{ot} + \kappa\left[\frac{1}{\theta^{\ell}}\log\left(CMA^{\ell}_{ot}\right) - \frac{1}{\theta^{c}}\log\left(CMA^{c}_{ot}\right)\right] + X_{ot} + u_{ot}\ ,$$

where X_{ot} are the additional controls.

Lastly, we take the difference within each neighborhood between years t and $t-1$:

$$\Delta \log\left(\frac{R^{\ell}_{ot}}{R^{c}_{ot}}\right) = \alpha_t + \psi\Delta\log L^{\ell}_{ot} + \omega\Delta\log L^{c}_{ot} + \kappa\Delta\left[\frac{1}{\theta^{\ell}}\log\left(CMA^{\ell}_{ot}\right) - \frac{1}{\theta^{c}}\log\left(CMA^{c}_{ot}\right)\right] + \Delta X_{ot} + \tilde{u}_{ot}$$

where Δ represents the above first differences (within neighborhood, across years).

E.2 Residential Choice Elasticity η

Fixing values for the commuting and labor supply elasticities, we now discuss how to estimate the residential choice elasticity η. Recall that the probability of someone choosing to live in origin o in period t is defined as in Equation 5.

$$\pi_{o,t} = \left(\frac{B_{o,t}Q_{o,t}^{-(1-\beta)\eta}W_{o,t}{}^{\eta}}{\sum_{o'} B_{o',t}Q_{o',t}^{-(1-\beta)\eta}W_{o',t}{}^{\eta}}\right) ,$$

where $B_{o,t}$ is an unobserved residential amenity, $Q_{o,t}$ is the residential floor-space price, and $W_{o,t}$ is the origin-specific wage-index defined in Equation 6. Taking the log of both sides, we derive:

$$\ln\pi_{ot} = \ln B_{ot} - (1-\beta)\eta\ln Q_{ot} + \eta\ln W_{ot} - \ln(\sum_{o'} B_{o't}Q_{o't}^{-(1-\beta)\eta}W_{o't}{}^{\eta})$$

Redefining terms, including the unobserved residential amenity as part of an error term $\epsilon_{\eta,t}$, the corresponding estimation equation becomes:

$$\ln\pi_{o,t} = \eta(\ln W_{o,t} - (1-\beta)\ln Q_{o,t}) + \gamma_t + \gamma_o + \tilde{X}_{ot} + \epsilon_{\eta,t} ,$$

where we set $1-\beta = 0.25$ following Ahlfeldt et al. (2015) and γ_t are time-fixed effects, γ_o are neighborhood fixed effects, and $\tilde{X}_{ot}$ are additional controls.

Lastly, we take the difference within each neighborhood between years t and $t-1$:

$$\Delta\ln\pi_{o,t} = \eta\Delta(\ln W_{o,t} - (1-\beta)\ln Q_{o,t}) + \gamma_t + \Delta\tilde{X}_{ot} + \tilde{\epsilon}_{\eta,t} ,$$

where Δ represents the above first differences (within neighborhood, over time).

E.3 Crime Productivity Externality

To estimate the crime externality parameter λ, we follow Ahlfeldt et al. (2015) and derive moment conditions using the structural productivity residual. Using first-order conditions of the production function for the legitimate sector with respect to labor and floor space and the zero-profit condition, we derive the following structural relationship linking legitimate sector wages w^{ℓ}_{d}, the productivity residual $a^{\ell}_{d,t}$, land/factor prices $q^{\ell}_{d,t}$, crime externality $Y^{c}_{d,t} = \frac{L^{c}_{d,t}}{\bar{H}_{d,t}}$, and legitimate-sector externality $Y^{\ell}_{d,t} = \frac{L^{\ell}_{d,t}}{\bar{H}_{d,t}}$:

$$\left(\tilde{\alpha}^{1-\alpha^{\ell}-\zeta}\left(a^{\ell}_{d}(Y^{c}_{d})^{\lambda}\right)\left(\frac{1}{\bar{H}_{d}}\right)^{\zeta}(w^{\ell}_{d})^{-(\alpha^{\ell}+\zeta)} - (q^{\ell}_{d})^{1-\alpha^{\ell}-\zeta}(F^{\ell}_{d})^{-\zeta}\right) = 0\ ,$$

where $\tilde{\alpha} = (\alpha^{\ell})^{\frac{\zeta+(\alpha^{\ell})}{1-\alpha^{\ell}-\zeta}} - (\alpha^{\ell})^{\frac{1}{1-\alpha^{\ell}-\zeta}}$

Taking logs and differencing this expression from its geometric mean, gives us the following moment function:

$$-\Delta log\left(\frac{a^{\ell}_{d,t}}{\overline{a}^{\ell}_{t}}\right) = (\alpha^{\ell}+\zeta-1)\Delta log\left(\frac{q^{\ell}_{d,t}}{\overline{q}^{\ell}_{t}}\right) - (\alpha^{\ell}+\zeta)\Delta log\left(\frac{w^{\ell}_{d,t}}{\overline{w}^{\ell}_{t}}\right) - \lambda\Delta log\left(\frac{Y^{c}_{d,t}}{\overline{Y}^{c}_{t}}\right)\ ,$$

where $\overline{a}^{\ell}_{t}$, $\overline{q}^{\ell}_{t}$, $\overline{w}^{\ell}_{t}$, and $\overline{Y}^{c}_{t}$ are geometric means defined as $\overline{x_t} = exp(\frac{1}{S}\sum_{d=1}^{S} log(x_{dt}))$ and Δ differences out time-invariant aspects of productivity, so that Equation 15 has mean 0. We then arrive at the following moment condition:

$$\mathbb{E}\left[h(Z)\Delta log\left(\frac{a^{\ell}_{dt}}{\overline{a}^{\ell}_{t}}\right)\right] = 0\ , \tag{54}$$

where $h(Z)$ are our instruments and we divide both sides of the moment by a constant of -1.

E.4 Bartik Instrument Construction

We exploit exogenous variation in legitimate-sector employment across neighborhoods using a spatially-weighted Bartik instrument. Our approach builds on the equilibrium conditions in Equations 10, where productivity shocks affect local labor markets through both direct effects on local firms and indirect effects transmitted through commuting networks. We construct an instrument that captures how sector-specific productivity shocks propagate across neighborhoods via spatial linkages, generating plausibly exogenous variation in equilibrium employment.

Let z_{dt} denote the neighborhood-level Bartik shock to legitimate-sector productivity. We construct this shift-share instrument in two steps. First, we calculate annual city-wide employment and wage growth rates by economic sector using the PILA dataset. These growth rates, g_{st}, serve as our sector-specific macroeconomic shocks. Second, we interact these shocks with baseline neighborhood-level employment shares by sector, s_{ds,t_0}, to construct the instrument:

$$z_{dt} = \sum_{s} s_{ds,t_0} \cdot g_{st}$$

This approach generates cross-sectional variation through differences in initial industrial composition across neighborhoods. Neighborhoods with higher baseline exposure to subsequently growing (declining) sectors experience larger positive (negative) productivity shocks. The identifying assumption is that baseline sectoral composition is uncorrelated with subsequent neighborhood-specific shocks to the outcome variable, conditional on controls.

To account for spatial spillovers through commuting networks, we incorporate iceberg commuting costs τ_{odt}. These costs weight the transmission of productivity shocks: a shock in neighborhood d affects legitimate labor supply in neighborhood o inversely proportional to the commuting cost between them. This captures how increased labor demand from positive productivity shocks diffuses through the urban labor market according to commuting patterns. Our spatially-weighted instrument for neighborhood o is:

$$\tilde{z}_{ot} = \sum_d z_{dt}^{\theta^\ell} \tau_{odt}^{-\theta^\ell} \tag{55}$$

The weighting scheme follows directly from our market access framework, where the destination-level Bartik shocks are scaled by θ^ℓ, the legitimate-sector labor supply elasticity, reflecting how wages translate into market access changes.