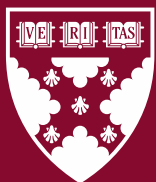


Working Paper 24-016

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Spatial Mobility, Economic Opportunity, and Crime

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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 system to 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 almost any neighborhood, 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

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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, 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, 2016; Tsivanidis, 2023; Zárate, 2022).

Yet, credibly estimating the parameters of the model raises a second set of challenges: We require detailed granular data and reliable variation for identification. We leverage the roll-out of a public transit system over a decade to identify our 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 and a tractable reduced-form analysis that does not rest heavily on the structure of the model.

¹See, 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.

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, and 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 reduced form evidence that these expansions decreased the likelihood that inhabitants of low-income, high-crime neighborhoods near the newly built stations were arrested for crimes, and that lower commute times predict higher legitimate employment. That is, inhabitants of segregated neighborhoods seemed to take advantage of new opportunities, as new cable lines improved access. Yet, these patterns exhibit stark heterogeneity by the baseline spatial distribution of economic opportunity and crime in newly connected neighborhoods. The reductions in crime 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 small 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, 2022), and estimate the effects of several transportation system expansions on the equilibrium level and spatial distribution of employment and crime. This framework allows us to overcome SUTVA violations, account for correlated neighborhood-level shocks when identifying parameters, and capture the rich heterogeneity in baseline access to different types of opportunities.²

We build on previous models in two important ways. First, we incorporate the role of crime, modeling the sectoral choice (between crime and legitimate employment) of individuals. Crime is unlike other forms of economic activity, as it affects both the functioning of legitimate businesses

²The Stable Unit Treatment Value Assumption is violated as all neighborhoods are indirectly affected when new transit lines are built.

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, while new legitimate economic activity changes the returns to crime. We identify these externalities by deriving variation from the onset of gang wars as a result of the extradition of drug lords to the US.³

The 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? What are the resulting net effects on aggregate crime and GDP, as well as inequality across neighborhoods? Which neighborhoods should we target for further expansions in transit access?

We simulate new cable lines that were officially proposed, but 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. As such, neighborhood segregation appears to be a meaningful driver of aggregate crime in the city. The counterfactual (proposed) lines we construct increase net GDP by 2.0 billion USD.

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.

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 the highest baseline legitimate-wage neighborhoods yields aggregate reductions in crime, and increases in output and welfare. The largest gains accrue when connecting 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 welfare. A transit subsidy reducing welfare runs contrary to other urban transit models. We show that these are driven by the fact that crime may have negative externalities on the legitimate sector, again highlighting the importance of modeling and measuring criminal participation with cross-sectoral spillovers.

Our work speaks to three distinct literatures. First, our results contribute to the crime

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

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 important insight into a spatial equilibrium model of commuting with both criminal and legitimate sectors. We examine how transportation infrastructure investments that connect previously segregated areas of criminal and legitimate economic activity affect both the spatial distribution and overall levels of crime.

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, 2016). Our study is closest to recent work by Tsivanidis (2023) and Zárate (2022), which uses these techniques to study similar expansions in urban transportation infrastructure. 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. 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 welfare.

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 relative returns to 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

⁴Prior 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).

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 from 2002, SISBEN II from 2005, and SISBEN III from 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 households 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, whether or not they were convicted. These data contain information on the type of crime committed, the date and neighborhood of arrest, and a unique identification number of the arrested individual. 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 the 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 information on payroll, earnings, days worked, firm and worker identifiers, and demographic information of employees. This is our measure of who is engaged in formal sector work, and how much they earn. As the PILA documents the locations of formal sector workers, we further supplement information from the Census 2005 and the SISBEN to measure overall legitimate activity (formal plus informal). The details are in [Appendix A.2](#).

To know the location of the workplaces, we obtain data from the *Camara de Comercio de Medellin* (Chamber of Commerce of Medellin), which is the census of all the firms formally registered with the government in Medellín between 2007 and 2018. This database contains identification numbers of statutory representatives, total assets and liabilities reported, and most importantly, the address of establishments. Informal establishments are from the underlying data in [Straulino et al. \(2022\)](#).

⁵While 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.

We construct the informal sector workforce, by first computing the rate of informal workers at the origin-level using the SISBEN (details in Appendix A). We begin with the number of residents at origin (scaling up the share of SISBEN population in the 2005 complete Census), and the number of criminals at origin (scaled up using the probability of being arrested). The number of informal workers at origin is the share of informal workers at origin (from SISBEN) times the number of legitimate workers at origin. Informal establishments are from the underlying data in [Straulino et al. \(2022\)](#), and using this database, we ascertain that the spatial distribution of formal and informal sector firms are highly correlated. The flows of legitimate workers (formal and informal) are estimated using the flows of formal workers using PILA.⁶

We augment these data with the Land Registry Data from Medellín’s Cadastre from 2006 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 Medellín 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, Jobs, and Crime in Medellín

3.1 Segregation and Urban Transit in Medellín

Located in the northwestern region of Colombia, Medellín is the second largest city after the capital, Bogotá. It has strong industrial and financial sectors with approximately 2.3 million people or 5.5% of the Colombian population. The urban zone consists of 269 neighborhoods, divided into 21 *comunas*, 5 of which are semi-rural townships (*corregimientos*).

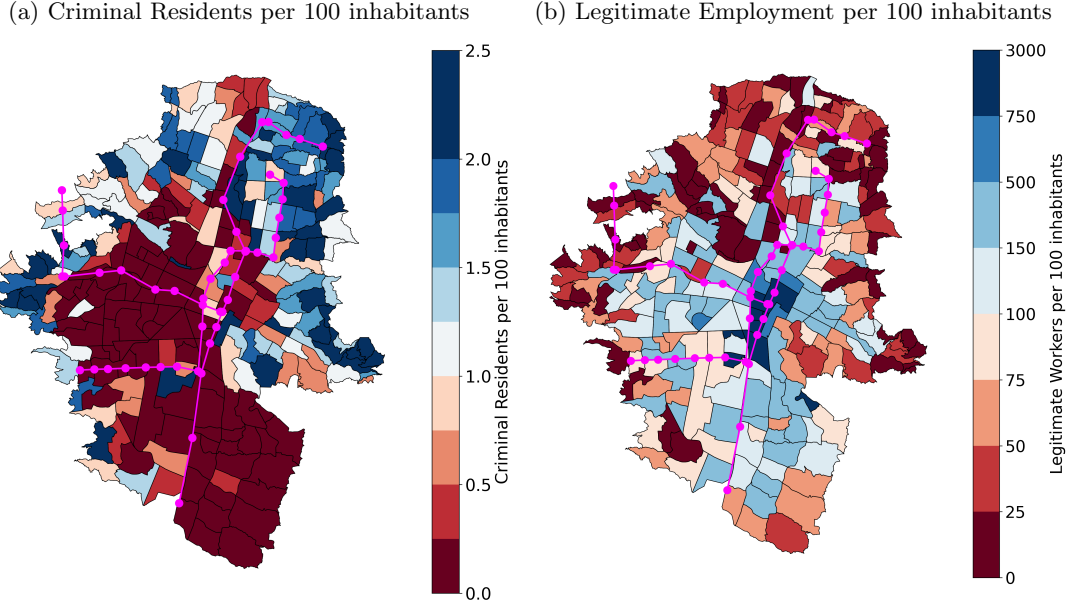
The city is starkly segregated in terms of where individuals live, work, and where criminal activity is prevalent. Figure 1 describes the spatial distribution of criminal activity and legitimate employment across the city in 2010, along with the transit lines that existed in 2010. Those involved in the criminal sector live in areas that were historically associated with drug cartels. These include the northeastern sections of the city, 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 south-eastern 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, most

⁶For formal workers, we measure where they live and work. For informal workers, we measure where they live, and where informal-sector establishments are distributed across the city.

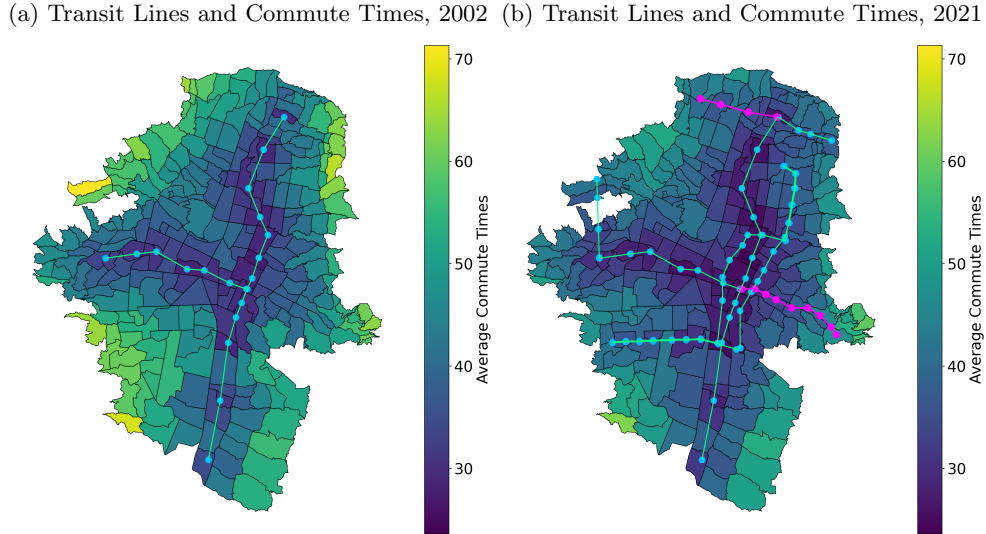
⁷We describe the construction of the transport network in Section A.3 of the Appendix.

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



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.

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



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.

notably in the southwest.

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 and 2008, an expanded metro in 2012, tramways in 2015, and a large Bus Rapid Transit (BRT) corridor over the 2012-15 period. Figure 2 describes the roll-out of the transit infrastructure over the course of our analysis period. 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.

3.2 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 B.1 from CCSPJP (2009)). The high crime rates reflect the presence of urban militias, local gangs, drug cartels, criminal bands, and paramilitaries.⁹ 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 sample period rates have fallen substantially from about 184 per 100,000 inhabitants in 2002 to about 21 (Figure B.1). We note, however, that this range is not only representative of many cities in Latin America, but also of many current 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

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

⁹*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).

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.¹⁰ Gangs also actively recruit idle youth that are *amurrao* (local slang, literally: ‘sitting on the wall’) and without a high-paying job.¹¹

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 mainly 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.”¹²

4 Descriptive and Reduced-form Relationships

4.1 Commute Times for Different Activities

We first describe certain features of our setting in relation to commute times and how changes in commute times affect the spatial distribution of crime and legitimate employment. To begin, consider Figure 3 that plots the commute times in our individual-level data for different types of criminal activity and for formal work. Figure 3 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.¹³

The differences in commute times have meaningful implications for what would happen

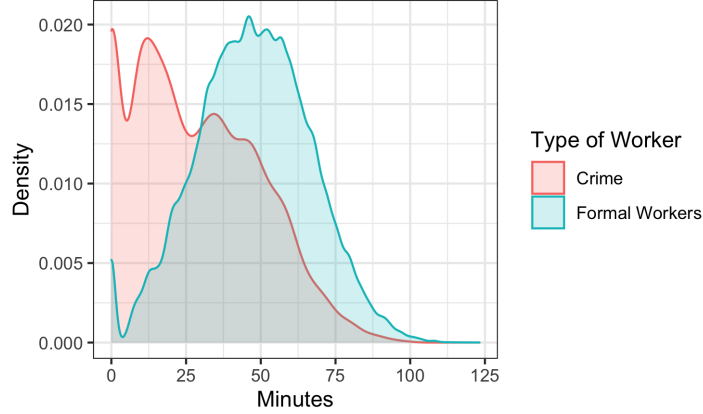
¹⁰See *interview with Gato, p264* and *interview with Armando, p197*.

¹¹Sector 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*).

¹²During the demobilization of militias in the mid-2000s, many were encouraged to join the formal sector, given identity cards and medical cards (Rozema, 2018).

¹³The 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. the first arrest in 2010 for the type of crime.

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 criminal activity than that on legitimate-sector employment. On the other hand, the densities may indicate that legitimate-sector work is strongly segregated and confined to certain pockets, and reaching those pockets requires a fair amount of commute time. New transit lines 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. As such, these patterns suggest that conditional on sector choice, those in crime may travel farther; but improving access to legitimate jobs may lead to a switch away from criminality.

4.2 The Effects of Cables 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.

Consider crimes committed in a neighborhood n . The neighborhood could either be a destination d for where the criminal activity occurred, or origin o for where criminals resided $n = \{d, o\}$. A simple difference-in-differences (DiD) design would suggest the following specification:

$$\text{Log}(\text{Crimes})_{nt} = \gamma_t + \gamma_n + \beta_1 (\text{Log}[\text{Dist to New Stations}]_n \times \text{Post}_t) + \epsilon_{1nt} \quad n = \{d, o\} \quad (1)$$

Here, γ_t are time fixed effects that control for changes in aggregate crime and transportation across neighborhoods, and γ_n are neighborhood fixed effects that account for time-invariant neighborhood-level differences. $\text{Log}(\text{Distance to New Stations})_n$ is the distance between the neighborhood and the closest new cable station. Post_t is an indicator for the period after when the new cable was built. As such, β_1 is the DiD estimator for the effect of being farther away from a newly built cable station on crime.

In the first two columns of Table C.1, panel A, we examine the changes to criminal activity at destinations, and in the first two columns of panel B, by the neighborhood of origin of the criminal. Given that some neighborhoods may have no crime at all, we estimate the equations using a Poisson Pseudo Maximum Likelihood (PPML) estimator, and cluster our errors at the neighborhood level.

The first two columns of panel A, Table C.1, suggest that when a neighborhood is better connected to a station, criminal activity in that neighborhood is lower, holding all else constant. Being farther away from the station is associated with higher levels of crime in the years subsequent to the opening of the transit line. This is true for all types of crime, including the subset of violent criminal activity.

The first two columns of panel B, Table C.1, present an interesting complementary result: when residences are connected to the cable, people from those neighborhoods are less likely to be arrested for criminal activity. As such, while panel A describes what happens to criminal destinations when connected to transit, panel B describes what happens to the criminal activity of those originating from such locations. Both suggest that locations closer to new stations see a fall in crime.

However, such an analysis ignores the rich dimensionality of the data. Indeed, if origins and destinations are close by, then it may be that origins and destinations display similar patterns. As such, by reformulating the data to be at the origin-by-destination-by-time level, we can control for time-invariant features of the origin-destination pair with comuna origin-destination fixed effect. Here, we can examine the impacts on crime as a consequence of changes to the distance to the nearest station at either the origin or the destination of criminal activity. In such specifications, to be conservative, we two-way cluster our standard errors at both the origin and destination level.

The last two columns of Table C.1 reinforce the previous results by showing that the closer one is to the new station, the greater the decrease in criminal activity once the new line is introduced. This is true for the destinations of criminal activity (the last two columns of panel A, Table C.1), and the originating residences of these criminals (last two columns of panel B, Table C.1).¹⁴

¹⁴One may be curious to know how policing and the probability of crimes leading to arrests changed with the introduction of the cable. To that end, we compile annual data on crime reports, and arrests made by type of crime and location. Interestingly, in Table B.3, we find that there is no change in the probability of a crime leading to an arrest when the cable was introduced. Yet, any estimation of parameters should still account for possible changes to policing, and we discuss below (first in Section 4.4) how controlling for origin-year and destination-year fixed effects allows us to do so.

Given the different possible countervailing effects, it may be that what determines the net effects of an expansion in the transportation infrastructure is how long it takes to reach the closest of the stations so as to access the broader transit network. In Appendix C, we explore if changes in the number of minutes to a station affect criminal activity. Table C.2 shows similar results to the ones presented in Tables C.1.

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. That is, in order to generalize these results to broader policies or interventions which 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.

4.3 Heterogeneity by Neighborhood Economic Structure

The fall in crime, on average, as a result of the cable expansion 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.

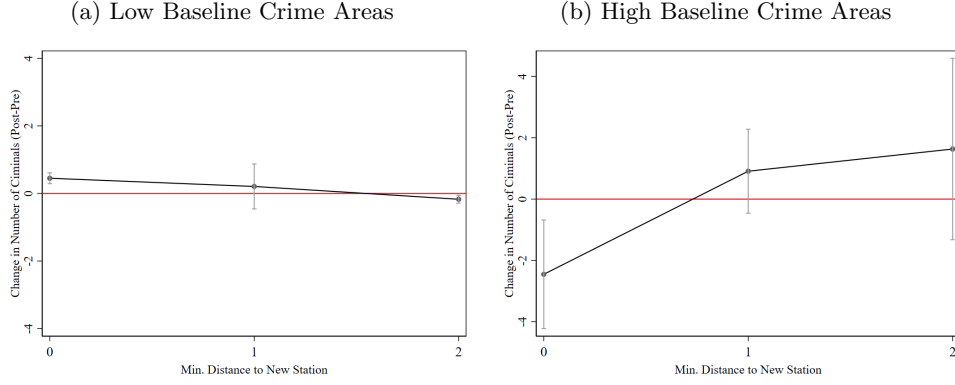
If most crime centers around local street gangs, then not being able to easily go to other parts of the city may mean that, in neighborhoods that have street gangs, youth will be drawn into crime. If so, to engage in crime, individuals in such neighborhoods stay in their neighborhoods, but to participate 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 Tables C.1 may depend on the underlying economic structure of the neighborhoods.

To examine this, we consider different aspects of heterogeneity that directly relate to our analysis: i.e., the role played by access to different types of opportunities. We combine all new stations and consider the change (post minus pre) in crime rates. To document the changes, we must aim to compare regions near the newly built stations to those farther away. Yet, we should not consider regions further away as ‘control neighborhoods,’ as all neighborhoods will be indirectly affected. To be transparent, we show the effects along various distance bins so as to non-parametrically describe these relationships.

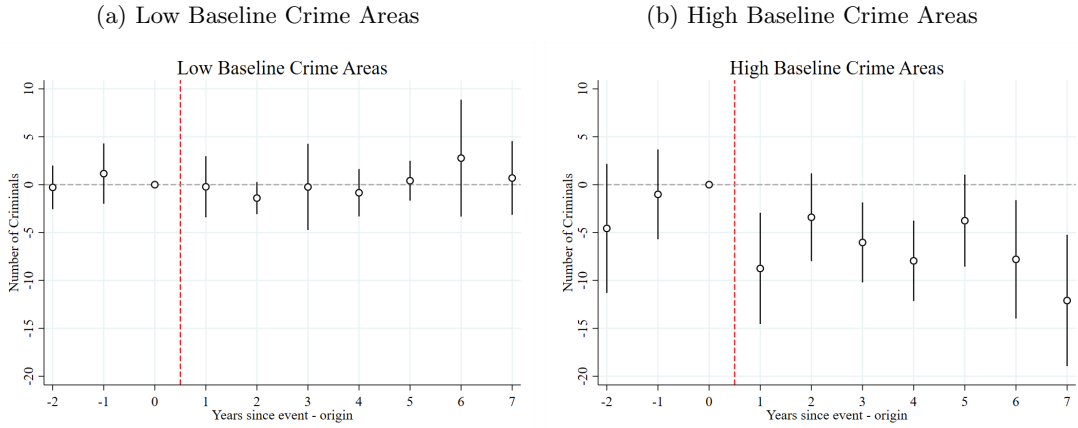
In Figure 4 we see that there were sharp reductions in criminal activity originating from

Figure 4: Changes in Crime at the Origin by Baseline Crime, and Distance (in km) Bins



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-cable 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 5: Changes in Crime Over Time at the Origin by Baseline Crime



Notes: Figures show event study plots of the change in non-drug related crime over time as a function of being 0 to 1km from a new station. Control neighborhoods are 1-2km from the station. 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.

neighborhoods near the stations (0-1km). Yet, this reduction is confined to neighborhoods that have high baseline levels of crime (right panel). If anything, the left panel suggests a mild increase in crime in areas that had low levels of baseline criminal activity. We also see a spatial redistribution of criminal activity: Even as crimes reduce in the proximity of stations in high-crime areas, there may be a mild increase in criminal activity about 2km away from the station.

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). In Figure C.1 we repeat the analysis using baseline income levels of the neighborhoods rather than baseline crime. We find a similar story (opposite pattern as expected). These are examples of the nuances we will need to include in our structural framework below.

To document the dynamics of the responses, by different types of crime and different types of baseline features of the neighborhoods, we conduct an event study style analysis. We pool the different cable lines, and compare crime outcomes both before and after the cable was opened, relative to the year it was opened. The years before allow us to test for pre-trends in our outcomes, whereas the years after document the dynamics of the changing relationship. For instance, one may be concerned that lines were placed to connect origins and destinations on a particular crime-reduction trajectory, which would then be visible in the pre-trends leading up to the establishment of the line.¹⁵

Figures 5 show no detectable effects for low baseline crime neighborhoods. Figure C.2 in the Appendix confirms that similar patterns exist when just focusing on violent crimes as a subset of non-drug crimes. This is reassuring because violent crimes are likely the most associated with criminal employment (Khanna et al., 2023).¹⁶

4.4 Panel Gravity Equations and Neighborhood-by-Time Shocks

So far, 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 *relative* to other neighborhoods. As neighborhoods are connected, these results may indeed also be driven by 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

¹⁵While we see no differential trends in the event study figures, in our analysis below, we also augment the specifications with high-dimensional fixed effects that control for differential shocks at origins, destinations, and time-invariant origin-destination features.

¹⁶Here, we focus on non-drug crimes because drug crimes include a large proportion of recreational use and possession. The main analyses include all crimes, including drug crimes, for completeness.

(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 the information on how travel times between any origin and destination neighborhood pair change as and when new cable lines are introduced. This variable *Travel Time Minutes_{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} :

$$\text{Log}(\text{Crimes})_{odt} = \gamma_{ot} + \gamma_{dt} + \gamma_{od} + \beta_2 \text{Travel Time Minutes}_{odt} + \epsilon_{2odt} \quad (2)$$

We return to this equation 2 later in our analysis as it helps causally identify the crucial parameters of our model. 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-by-destination pairs that were unaccounted for by the fixed effects. We show later that β_2 is structurally informative of crucial economic elasticities that drive the spatial distribution of crime and legitimate activity across the city.

In Table 1, we estimate equation 2. We confirm that 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 elasticities with respect to travel time are -0.0676 for all crimes, and a similar -0.0644 for violent crimes. However, as we show below 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 lower overall criminality. In the

Table 1: 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*** (0.0034)	-0.0644*** (0.0064)	-0.0386*** (0.0078)
Observations	1,157,776	1,157,776	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 pseudo maximum likelihood (PPML) with high dimensional fixed effects, and two-way cluster our errors at the origin and destination level.

last column of Table 1, 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 1 below and discuss how β_3 informs our model’s parameters.

One may also expect that gang boundaries affect the commuting elasticity. We estimate this gravity equation again, interacting the commuting time with an indicator for whether the commute crosses a gang boundary. Table B.1 shows that in the context of Medellín, gang boundaries do not seem to affect the commuting elasticity for either crime or legitimate sector work. One may also consider the possibility, that these elasticities vary by type of crime. Table B.2 shows that the elasticities are similar in magnitude across different types of crime, especially for crimes that are likely to be associated with criminal enterprises (Khanna et al., 2023).

5 Model

Understanding how urban transportation investments impact criminal participation across neighborhoods and, in turn, how such participation affects 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); rather, other neighborhoods will also be affected as criminals and workers change their commute patterns across the city.

To overcome these challenges, and to study the general equilibrium implications of criminal activity within cities, we build on recent developments in the economic geography literature by outlining an urban quantitative model with crime. We adapt recent urban spatial models (Ahlfeldt et al., 2015; Heblich et al., 2020), to incorporate the role of criminal activity and the externalities this activity could have on other parts of the economy. We model the sectoral choice (between crime and legitimate employment) of individuals as a function of firm market access and commuter market access (Zárate, 2022).

Incorporating a ‘non-productive’ sector like crime introduces additional nuances. We draw inspiration from recent studies highlighting externalities in spatial models (Heblich et al., 2021; Tsivanidis, 2023). We incorporate inter-sectoral spillovers, whereby crime may have negative externalities on other forms of economic activity, such as legitimate employment, as well as on neighborhood amenities (Almagro and Domínguez-Iino, 2022). These inter-sectoral spillovers potentially create feedback loops – more crime in a neighborhood lowers legitimate-sector productivity, which in turn reduces the legitimate-sector wage and induces more criminal participation. Additionally, legitimate economic activity affects the returns to crime as well by changing the rents to extortion and burglary.

Consider a city embedded within a wider economy. The city consists of a set of discrete neighborhoods that are indexed by o and d , where $o, d \in \mathcal{N} \equiv \{1, \dots, N\}$. These neighborhoods are populated by an endogenous measure of \bar{H} workers who are perfectly mobile within the city and the larger economy. Workers are risk neutral and have preferences for housing (H) and consumption of a final good (C). They can participate in two sectors indexed by $s \in \{c, \ell\}$, where c and ℓ stand for crime and legitimate sectors, respectively. A worker ω choosing neighborhoods o and d as living and working destinations, respectively, and choosing to work in sector s maximizes the following utility

$$U_{ods\omega} = \frac{\epsilon_{ods\omega}}{\tau_{od}} \left(\frac{C_{ods}}{\beta} \right)^\beta \left(\frac{H_{ods}}{1-\beta} \right)^{1-\beta}, \quad (3)$$

where C_{ods} is consumption of the final good and it is taken as a numeraire, H_{ods} represents housing consumption, $\tau_{od} \geq 0$ is an iceberg commuting cost incurred by the consumer when moving from origin o to destination d , $\epsilon_{ods\omega}$ is an idiosyncratic shock, and $\beta \in (0, 1)$ is the expenditure share on the consumption of the final good.¹⁷ The shock $\epsilon_{ods\omega}$ represents idiosyncratic preferences that motivate individuals to choose different locations, o and d , and different working sector s , even when their observable characteristics are the same.

We assume that the term ϵ_{ods} is drawn from a nested Frechet distribution:

$$H(\vec{\epsilon}) = \exp \left[- \sum_o B_o \left(\sum_s B_{os} \left(\sum_d \epsilon_{ods\omega}^{-\theta_s} \right)^{\frac{\kappa}{\theta_s}} \right)^{\frac{\eta}{\kappa}} \right], \quad \eta < \kappa < \theta_s, \quad s \in \{c, \ell\}, \quad (4)$$

¹⁷Iceberg commuting costs affect utility directly, but this specification is isomorphic to one in which commuting costs reduce effective wages earned by individuals due to the time used for commuting.

where the parameters η , κ , and θ_s control the dispersion of the idiosyncratic shock across residences, sectors, and workplaces, respectively. The parameters B_o and B_{os} can be thought of as origin and origin-sector-specific amenities that attract individuals to different origins/origin-sectors. Given the observed shocks, individuals decide where to reside, in which sector to work, and where to work.

Using the properties of the Frechet distribution, the probability of living in o , working in sector s , and commuting to destination d is:

$$\pi_{ods} = \underbrace{\left(\frac{B_o Q_o^{-(1-\beta)\eta} W_o^\eta}{\sum_{o'} B_{o'} Q_{o'}^{-(1-\beta)\eta} W_{o'}^\eta} \right)}_{\equiv \pi_o} \underbrace{\left(\frac{B_{os} W_{os|o}^\kappa}{\sum_{s'} B_{os'} W_{os'|o}^\kappa} \right)}_{\equiv \pi_{os|o}} \underbrace{\left(\frac{w_{ds}^{\theta_s} \tau_{od}^{-\theta_s}}{\sum_{d'} w_{d's}^{\theta_s} \tau_{od'}^{-\theta_s}} \right)}_{\equiv \pi_{ods|os}}, \quad (5)$$

where Q_o is the residential floorspace price in neighborhood o , $W_o \equiv \left(\sum_{s'} W_{os'|o}^\kappa \right)^{1/\kappa}$ is an origin-specific wage index, $W_{os|o} \equiv \left(\sum_{d'} w_{d's}^{\theta_s} \tau_{od'}^{-\theta_s} \right)^{1/\theta_s}$ is an origin-sector specific wage index, and w_{ds} is the worker's wage for working in sector s in destination d .

The nested Frechet assumption allows us to decompose the overall probability of choosing an origin-sector-destination into three different components: $\pi_{ods|os}$, the probability of choosing a destination d conditional on having chosen an origin and a sector; $\pi_{os|o}$, the probability of choosing a sector conditional on your origin; and π_o , the probability of choosing an origin o . Note that $\sum_d \pi_{ods|os} = \sum_s \pi_{os|o} = \sum_o \pi_o = 1$.

The destination choice probability $\pi_{ods|os}$ (in equation 5) implies that, conditional on having chosen an origin and a sector, individuals are more likely to work in a destination that has a large commute-discounted return $w_{ds}^{\theta_s} \tau_{od}^{-\theta_s}$ relative to the other destinations d' . The sector choice probability $\pi_{os|o}$, conditional on their origin o , implies individuals are more likely to choose a sector if their neighborhood of origin has large sector-specific amenity B_{os} , and if they live close to profitable destinations in that sector, $W_{os|o}$, relative to the other sector s' . Here $W_{os|o}$ essentially captures the option value of being employed in sector s . Finally, from π_o individuals are more likely to choose an origin neighborhood o if it has large amenities B_o , low residential floorspace prices Q_o , and if it is close to destinations that are generally profitable W_o , relative to all other origins o' .

Workers are mobile between the city and the larger economy, which delivers a constant utility \bar{U} . Defining V_{ods} as the indirect utility function of living in o working in d and participating in sector s , spatial equilibrium requires expected utility equalization:

$$\bar{U} = \mathbb{E} \left[\max_{ods} \{V_{ods}\} \right] = \Gamma \left(\frac{\eta-1}{\eta} \right) \left(\sum_o B_o \left[Q_o^{-(1-\beta)} W_o \right]^\eta \right)^{1/\eta}, \quad (6)$$

where $\Gamma(\cdot)$ is the gamma function.

5.1 Production

We assume that there is a single final good, the numeraire, that is costlessly traded within the city and the larger economy. Final good production occurs under conditions of perfect competition and constant returns to scale, with a Cobb-Douglas technology. Output of the final good in block d , y_d is:

$$y_d = A_{d\ell} (H_{Ed\ell})^\alpha (L_{d\ell})^{1-\alpha} ,$$

where $A_{d\ell}$ is final goods productivity, $H_{Ed\ell}$ is workplace legitimate employment, $L_{d\ell}$ is commercial floorspace in destination d , and $\alpha \in (0, 1)$ is the legitimate employment share. Commercial floorspace can be rented at a price q_d .

Firms choose their inputs of workers and commercial floorspace to maximize profits, taking as given final goods productivity $A_{d\ell}$, the distribution of idiosyncratic utility, goods, and factor prices $w_{d\ell}, q_d$, and the location decisions of workers. Combining the FOCs of the firm with respect to legitimate employment and commercial floorspace for a firm in block d delivers:

$$q_d = (1 - \alpha) \left(\frac{\alpha}{w_{d\ell}} \right)^{\alpha/(1-\alpha)} A_{d\ell}^{1/(1-\alpha)}, \quad (7)$$

which relates commercial floorspace prices to wages and productivity in each neighborhood.

5.1.1 Floorspace Market

We assume that there is a competitive floorspace market at each destination. A competitive floor-space provider allocates its total floorspace, L_d , by choosing a fraction $\varrho_d \in [0, 1]$ for commercial floorspace and $(1 - \varrho_d)$ for residential floorspace to maximize total profits. Income from land goes to absentee landlords and is not spent in the city, as in [Ahlfeldt et al. \(2015\)](#); [Heblich et al. \(2021\)](#). This firm takes as given commercial and residential prices, q_d and Q_d , respectively, as well as a tax equivalent land use regulation $\xi_d \geq 1$ that increases the overall price of residential housing to $Q_d \xi_d$. The firm's problem is:

$$\max_{\varrho_d \in [0, 1]} \varrho_d L_d q_d + (1 - \varrho_d) L_d \xi_d Q_d$$

This yields no arbitrage condition, whereby $\varrho_d = 1$ if $q_d > \xi_d Q_d$, while $\varrho_d \in [0, 1]$ if $q_d = \xi_d Q_d$, and $\varrho_d = 0$ if $q_d < \xi_d Q_d$.

Floor space L_d is supplied by a competitive construction sector that uses land, K_d , and capital, M_d , as inputs. Given the price of the best use of floorspace $\mathbb{Q}_d \equiv \max\{q_d, \xi_d Q_d\}$, as well as the price of land, \mathbb{R}_d , and the price of capital, \mathbb{P} , the firm solves:¹⁸

¹⁸We assume that there is a perfectly elastic supply of capital such that there is an exogenous price of capital \mathbb{P} that does not vary by neighborhood.

$$\max_{M_d, K_d} \quad \mathbb{Q}_d M_d^\mu K_d^{1-\mu} - \mathbb{P} M_d - \mathbb{R}_d K_d.$$

Residential land market clearing implies that the demand for residential floor space equals the supply of floor space allocated to residential use in each location $(1 - \varrho_d) L_d$. Using utility maximization for each worker and taking expectations over the distribution for idiosyncratic utility, residential floor market clearing is:

$$\mathbb{E}[\ell_{ods}|o] H_{Ro} = (1 - \varrho_o) L_o, \quad (8)$$

where H_{Ro} is the total residents living in o , and $\mathbb{E}[\ell_{ods}|o]$ is their expected housing demand.

Commercial land market clearing requires that demand for commercial floor space, which is obtained from the firm maximization problem, equals the supply of floor space allocated to commercial use in each location $\varrho_d L_d$. The commercial land market clearing condition is:

$$\left(\frac{(1 - \alpha) A_{d\ell}}{q_d} \right)^{1/\alpha} H_{Ed\ell} = \varrho_d L_d. \quad (9)$$

5.2 Crime Sector and its Effect on Productivity & Amenities

We assume that returns to crime are endogenous and given by:

$$w_{dc} = (1 - p_d) A_{dc} H_{Edc}^\rho H_{Ed\ell}^\iota, \quad (10)$$

where H_{Edc} and $H_{Ed\ell}$ are the total number of criminals and legitimate workers working in d , respectively, ρ regulates congestion (or agglomeration) forces in crime at a destination by which it is harder (easier) to commit crimes when there are already a lot of criminals in a location, and ι captures the fact that crime might be more or less profitable in locations in which there are a lot of legitimate employees.¹⁹ An important feature of criminal activity as a sector is that a lot of the ‘output’ may be non-productive. Returns are often earned via extortion/burglary ($\iota > 0$), or via drug production that is often ‘consumed’ abroad (in this case, the US).

The term p_d is a destination-specific exogenous probability of getting caught, and A_{dc} is the exogenous productivity of criminals in destination d . We use an empirical estimate of the probability of getting caught at a destination p_d by using the average homicide arrest rates at each destination across our sample. We use the homicide arrest rate since we can obtain the true measure of all homicides that occurred in each neighborhood, which we can then match to our arrest data to obtain the total number of captured criminals related to those homicides.²⁰

¹⁹This specification nests a simpler model in which returns to crime are exogenous when $\rho = \iota = 0$.

²⁰As shown in Figure B.2 the average arrest rate is low, 47.6%. In this sense, using this empirical estimate of the probability of capture allows us to convert observed captured criminals into the total number of criminals working in each destination.

Motivated by the literature on crime (Bryan et al., 2020; Melnikov et al., 2022; Rozo, 2018), we allow for crime to have a negative effect on the productivity of firms at a destination. Specifically, overall productivity, $A_{d\ell}$, at destination d is given by:

$$A_{d\ell} = a_{d\ell} \Upsilon_{dc}^\lambda,$$

where $a_{d\ell} > 0$ is the fundamental and exogenous component of productivity, and Υ_{dc} is an endogenous component of productivity that captures negative spillovers of crime to productivity in the legitimate sector in destination d . $\lambda \leq 0$ is a parameter that captures how important these negative spillovers are for the legitimate sector. We model these negative externalities as:

$$\Upsilon_{dc} \equiv \frac{H_{Edc}}{K_d}, \quad (11)$$

where H_{Edc} is the total number of criminals, and K_d is the total land area in destination d .²¹

In addition to allowing for crime to impact productivity in a neighborhood, we also allow the relative sector-specific residential amenities $\frac{B_{o\ell}}{B_{oc}}$ to vary with criminal sector activity in a given neighborhood:

$$\frac{B_{o\ell}}{B_{oc}} = b_{o\ell} \Upsilon_{oc}^\omega. \quad (12)$$

where $b_{o\ell} > 0$ is the fundamental and exogenous component of relative amenities, and Υ_{oc} is an endogenous component that captures the effect of having more crime on the sectoral composition of a neighborhood, and is mediated by the parameter $\omega \leq 0$. This implies that relative amenities are endogenous to the amount of crime that occurs in a location, and it underscores the fact that crime can reduce the desirability of a residential location for legitimate workers as has been found in the urban literature of crime (Cullen and Levitt, 1999; Gibbons, 2004).

5.3 Equilibrium

Given model parameters $\{\kappa, \theta_\ell, \theta_c, \eta, \beta, \alpha, \mu, \delta, \lambda, \iota, \rho, \omega\}$, the reservation utility in the wider economy \bar{U} , vectors of exogenous location characteristics $\{\mathbf{b}_\ell, \boldsymbol{\varphi}, \mathbf{K}, \boldsymbol{\xi}, \boldsymbol{\tau}, \mathbf{a}_\ell, \mathbf{p}_d, \mathbf{A}_c\}$ the general equilibrium of the model is given by the vectors $\{\mathbf{w}_\ell, \mathbf{w}_c, \mathbf{q}, \mathbf{q}, \mathbf{Q}, \mathbf{A}_\ell, \mathbf{B}_\ell, \boldsymbol{\pi}\}$, and total city population \bar{H} such that the population mobility condition (6) holds, origin and sector probabilities are given by choice probabilities in (5), there is legitimate labor market clearing, there is commercial (9) and residential (8) land markets clearing, criminal wages are endogenously determined by

²¹We also experimented with modeling these externalities with an iceberg spillover term as in Ahlfeldt et al. (2015) to capture the fact that crime in one neighborhood could affect productivity in an adjacent neighborhood:

$$\Upsilon_{dc} \equiv \sum_{k=1}^D e^{-\nu \tau_{dk}} \frac{H_{Ekc}}{K_k}$$

where ν is a parameter that captures how relevant crime at different distances is for productivity, and τ_{dk} are the iceberg commuting costs between blocks d and k . We estimated strong rates of decay leading to similar results to our baseline model.

equation (10), firms make zero profits, and there is no arbitrage between alternative uses of land.

In Appendix D.1, we have a broader discussion of the model's equilibrium. In Appendix D.3, we study a special case of two neighborhoods, and examine further when reductions in transportation costs τ_{od} will import opportunities (lower H_{Roc}) or export crime (increase H_{Eoc}). We particularly examine the roles played by our primary parameters of interest as a function of changing τ_{od} , in comparative static exercises: the sector choice parameter κ , the spillover externality λ , and transportation elasticities θ_s .

5.4 Welfare Decomposition

When considering aggregate legitimate and criminal welfare (“worker welfare”) for the entire city, we assume a utilitarian social planner evaluates aggregate welfare changes as:

$$\bar{U} = \sum_o \tilde{\omega}_o B_o (W_o Q_o^{-(1-\beta)})^\eta, \quad (13)$$

where $\tilde{\omega}_o$ is the welfare weight given to workers living in location o . As in Zárate (2022), these weights reflect variation in incomes across different neighborhoods. Let us define \bar{y}_o to be the total income of workers in location o , and $y_{d\ell}$ the total legitimate output produced in location d . This utility function then yields the following decomposition (to a first-order approximation):

$$\begin{aligned} d \log \bar{U} = & \underbrace{- \sum_o \sum_s \sum_d \bar{y}_o \pi_o \pi_{os|o} \pi_{ods|os} d \log \tau_{od}}_{\text{“Direct” Effect}} \\ & + \underbrace{\frac{\omega}{\kappa} \sum_o \sum_s \bar{y}_o \pi_o \pi_{os|o} d \log(H_{Eoc}) + \lambda \sum_d y_{d\ell} d \log(H_{Edc})}_{\text{“Externality” Effect}} \\ & + \underbrace{\rho \sum_d w_{dc} H_{Edc} d \log H_{Edc} + \iota \sum_d w_{dc} H_{Edc} d \log(H_{Ed\ell})}_{\text{Criminal Rents}} - \underbrace{\sum_o Q_o L_o d \log(Q_o)}_{\text{Landlord rents}} \end{aligned} \quad (14)$$

The “Direct” Effect captures changes to worker welfare from changes in commuting costs, equal to the total effect in an efficient economy without crime or absentee landlords (Baqae and Farhi, 2020). The “Externality” Effect allows for externalities criminals impose on legitimate sector workers at the origin in terms of amenities $\frac{\omega}{\kappa} \sum_o \sum_s \bar{y}_o \pi_o \pi_{os|o} d \log(H_{Eoc})$ and destination in terms of firm productivity $\lambda \sum_d y_{d\ell} d \log(H_{Edc})$. This effect will be larger when crime is committed in locations where there is larger production of the tradable good as it will decrease the productivity of firms located there, and when crime is prevalent where worker income resides, as individuals will see a reduction in their amenities. Criminal rents reflect how the returns to crime vary with the number of criminals competing for criminal opportunities and the number of formal sector workers exposed to crime. This effect arises due to the fact that crime acts as a non-productive activity in this economy. Finally, landlord rents reflect our assumption of absentee landlords.

The “Externality” effects and criminal rents (via ι) allow for cross-sectoral spillovers that affect the efficiency of the whole economy. Our expression indicates that for $\frac{\omega}{\kappa} < 0$, $\lambda < 0$ and sufficiently large in magnitude, even a small change in the number of criminals in each origin and destination has the potential to decrease total worker welfare. In particular, all legitimate sector workers would face welfare losses from both the residential and productivity effects. Furthermore, our specification of criminal rents allows these externalities to indirectly feed back into the returns to crime by reducing worker legitimate sector payoffs and, consequently, the number of legitimate sector workers. We provide the derivation of this decomposition in Appendix D.4.

6 Parameter Estimation

Our parameter estimation relies on panel variation coming from changes in the commuting network, crime, and economic shocks over time. As such, we include an additional time index t when writing our estimation specifications. Our theoretical model generates estimable specifications that we take directly to the data. We estimate sector-specific commuting elasticities, the sectoral labor supply elasticity, the residential choice elasticity, and parameters governing our cross-sectoral externalities sequentially.

The challenges to identifying our elasticity parameters come from our estimating equations representing equilibrium relationships that also depend on unobserved amenities and productivities. We resolve these challenges using fixed effects and shift-share instruments capturing exogenous productivity shocks.

6.1 Sector-Specific Commuting Elasticities

Following the literature, iceberg commuting is an exponential function of commuting time:

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

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 .

To estimate commuting elasticities, we use the fact that we observe worker flows across neighborhoods for both criminal and legitimate-sector workers. The joint origin-destination-sector probabilities described in equation 5 capture the probability of commuting to destination d conditional on living in origin o and working in sector s . Using this relationship, we derive the following gravity equation relating commuting flows across municipalities and iceberg costs:

$$\log(\pi_{ods|os,t}) = \underbrace{\beta_s}_{\delta \cdot \theta_s} \cdot \text{time}_{od,t} + \gamma_{o,t} + \gamma_{d,t} + \gamma_{od} + \tilde{\epsilon}_{ods,t} \quad (15)$$

$\pi_{ods|os,t}$ is the share of workers that commute to location d from o working in sector s in year t . $\text{time}_{od,t}$ is the average commuting time across municipalities od in year t ; $\gamma_{o,t}$ are origin-time fixed effects; $\gamma_{d,t}$ are destination-time fixed effects; γ_{od} are origin-destination comuna fixed

effects; and $\tilde{\epsilon}_{ods,t}$ captures measurement error in the observed $\pi_{ods|os,t}$.

We leverage the rollout of the cable to derive exogenous variation in $time_{od,t}$, and as such, Equation 15 does not directly relate two equilibrium objects. Since we observe variation across origin-destination pairs over time, we address the endogeneity underlying our commuting flows gravity equation 15 using origin-time, destination-time, and origin-destination comuna fixed effects. The former addresses unobserved residential neighborhood amenities, and the latter addresses unobserved destination-specific productivity shocks, including changes to the local economy, policing, and gang wars. The comuna origin-destination fixed effects account for time-invariant features of the location pairs.

Our goal is to recover θ_s , given β_s and δ_d . We estimate this equation via PPML to include zero commuting flows between municipalities in Table 1. Using a value of $\delta = 0.01$ taken from the literature (Tsivanidis, 2023; Zárate, 2022), we find a criminal commuting elasticity to be $\hat{\theta}_c = 6.76$ (SE: 0.34) and a legitimate sector commuting elasticity $\hat{\theta}_\ell = 3.86$ (SE: 0.78). Our estimates indicate that those in the criminal sector are relatively more sensitive to commuting times than those in the legitimate sector. This aligns with the literature on commuting elasticities in Latin America. Tsivanidis (2023) finds a commuting elasticity of 3.3 for low-skill workers and 2.72 for high-skill workers in Bogotá, and Zárate (2022) estimates commuting elasticities of 4.4 for informal workers and 3.11 for formal workers in Mexico City. The criminal sector is more similar to the low-skill and informal sectors in that participants in these sectors generally have lower levels of education. Given that crime is illegal, and often localized, it is also plausible that those in this sector are even more sensitive to commuting times than low-skill or informal workers.

6.1.1 Sectoral Labor Supply Elasticity

Taking the commuting elasticities as given, we now discuss how we recover κ , which corresponds to the labor supply elasticity across sectors that governs the reallocation of workers from the criminal sector to the legitimate-sector economy. To capture a measure of the average of worker access to wages weighted by travel time, we define the sector-specific commuter market access (CMA) for location n , sector s as :

$$CMA_{os,t} \equiv \sum_d w_{ds,t}^{\theta_s} \tau_{od,t}^{-\theta_s} , \quad (16)$$

which is an index of accessibility of jobs in location o to employment in sector s and captures whether workers that live in o have good access to jobs from sector s . We also define:

$$FMA_{ds,t} \equiv \sum_o \frac{\tau_{od,t}^{-\theta_s}}{CMA_{os,t}} H_{Ros,t} ,$$

as firm market access (FMA). We discuss how to recover $CMA_{os,t}$ and $FMA_{ds,t}$ from a just-identified system of equations in Appendix D.2.

To arrive at estimation equations containing sector-choice elasticity κ , recall that the sector

s choice probability in time period t conditional on being in origin o is:

$$\pi_{ost|o} = \frac{H_{os,t}}{H_{ol,t} + H_{oc,t}} = \frac{B_{os,t} CMA_{os,t}^{\kappa/\theta_s}}{\sum_{s'} B_{os',t} CMA_{os',t}^{\kappa/\theta_s}},$$

where the first equality holds by definition and the second equality comes from equation 5. Taking logs of both sides, we arrive at:

$$\ln(\pi_{ost|o}) = \ln(H_{os,t}) - \ln(H_{ol,t} + H_{oc,t}) = \frac{\kappa}{\theta_s} \ln(CMA_{os,t}) + \ln(B_{os,t}) - \ln\left(\sum_{s'} B_{os',t} CMA_{os',t}^{\kappa/\theta_s}\right)$$

This yields a regression equation *specific to sector s* that would allow us to identify κ :

$$\ln(\pi_{ost|o}) = \kappa \frac{1}{\theta_s} \ln(CMA_{os,t}) + \gamma_o + \gamma_t + \eta_{ost} \quad (17)$$

Intuitively, κ captures a sector-choice elasticity. When the option value of participating in sector s (captured by $CMA_{os,t}$) increases, more individuals choose to participate in sector s .

OLS estimates of κ would be biased as the sector shares we observe reflect equilibrium choices based on equilibrium wages, which, in turn, depend on sector-specific labor supply and demand. Unobserved residential amenities affect supply, as an individual's choice of origin affects her choice of work. Thus, $\ln(\pi_{olt|o})$ and $\frac{1}{\theta_\ell} \ln CMA_{ol,t}$ are correlated due to shifts of the relative labor supply curve in addition to shifts along the relative labor supply curve from changes in labor demand. κ , as an elasticity, is meant to describe shifts along the curve. If we include variation from shifts of the entire relative labor supply curve, our estimate of κ will be biased.

We estimate κ using a shift-share design, where we derive variation in neighborhood-level exposure to industry-specific productivity shocks (Bartik instruments) that shift out labor demand in the city, but are orthogonal to other determinants of labor supply. The labor-demand shifts trace out the labor supply curve, and identify κ . We rely on the fact that different neighborhoods have different industrial composition, and these industries see differential wage growth over time. We derive the differential wage growth at the industry level using wages only from other parts of Colombia (excluding Medellín). These external productivity instruments serve as relative labor demand shifters; legitimate sector firms experiencing exogenous productivity shocks will adjust wages and employment in Medellín accordingly. Shifts in only legitimate labor demand capture relative employment and wages along the same relative labor supply curve. Thus, our LATE in equation 17 will reflect only variation from shifts along relative supply, allowing us to identify κ . Our implementation follows the latest methods outlined by [Borusyak et al. \(2022\)](#), and we estimate a shock-level regression and report exposure-robust standard errors.

These Bartik instruments will correspond to *destinations* in our data, whereas equation 17 is estimated at the *origin* level. Consequently, we need to determine the degree to which residents in each origin were exposed to these destination-level shocks by using how connected residents in an origin were to each destination. To do this, we use equation 32 to motivate origin-level

instruments defined in equation 18, where z_{dt} is the destination level shock to legitimate-sector productivity and \tilde{z}_{ot} captures shocks aggregated to the origin level. The iceberg commuting value τ_{odt} serves as a weight such that productivity shocks in destinations d better connected to origin o affects residents making labor supply decisions in o more.

$$\tilde{z}_{ot} = \sum_d z_{dt}^{\theta_\ell} \tau_{odt}^{-\theta_\ell} \quad (18)$$

We estimate $\hat{\kappa} = 2.374$, displayed in the first column of Table 2. This estimate relies on variation in the calculated returns to only legitimate work, and there is a strong first stage.²² Zárate (2022)’s estimated labor supply elasticity across Mexico City’s informal and formal sectors are between 1.6 and 2.6.²³ Our legitimate sector includes informal labor as well, and our parameter is similar in magnitude.

Table 2: Estimating $\kappa, \eta, \lambda, \omega, \rho, \iota$

	(1) κ Log (Legitimate)	(2) η Log(Residents)	(3) λ Log(Productivity)	(4) ω Log(Amenity)	(5) $\rho \ \& \ \iota$ Log (Crime/Total)+ $\theta_C \delta_{od}$
Log CMA _{tot}	2.374*** (0.593) [0.926]				
Log $\frac{Welfare_o}{Rent_o^{1-\beta}}$		1.661 (1.358) [0.586]			
Log Crime _o			-0.062*** (0.0104)	-0.146*** (0.0251)	-0.227*** (0.0160)
Log Legitimate _o					0.146*** (0.0176)
Observation Level	Origin-Year	Origin-Year	Destination	Origin	Origin-Destination-Year
Method	BHJ	BHJ	GMM	GMM	2SLS
Instrument(s)	Shift-Share	Shift-Share	Don Berna	Don Berna	Shift-Share, Don Berna
F-Stat (of IV)	102.226	31.307			300.1
Fixed Effects	Origin, Year	Origin, Year			Origin, Year
Observations	1,614	2,152	260	260	1,157,776
SE Cluster	No	No	Destination	Origin	Destination

Notes: Table shows the estimation of additional parameters. Log CMA_{tot} is the natural log of legitimate-sector commuter market access values by neighborhood. Log Crime_o is the number of crimes in a neighborhood. Log Legitimate_o is the number of legitimate-sector workers in a neighborhood. The outcome in the last column is the crime-share adjusted for commute costs (Log(Crime/Total) + $\theta_C \delta_{od}$). For our shift-share design, we use the methods outlined in Borusyak et al. (2022) (BHJ), to obtain shock-level regressions and exposure robust standard errors. In columns 1 and 2 we report in parenthesis the BHJ standard errors and in squared brackets the IV standard errors. * Indicates significance at 10% level, ** indicates significance at 5% level, *** Indicates significance at 1% level.

²²As robustness, since taking a log of a small number magnifies error, we also estimate:

$$\ln(H_{ost|o}) = \kappa \frac{1}{\theta_s} \ln(CMA_{os,t}) + \gamma_o + \gamma_t + \eta_{ost}$$

which yields similar results. This specification puts $\ln(H_{ol,t} + H_{oc,t})$ in the error term, since it varies simultaneously by both origin and period.

²³Other papers that estimate cross-sectoral labor supply elasticities such as Galle et al. (2023) also find parameter values within this range.

6.2 Residential Choice Elasticity.

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 $W_{o,t} = (\text{CMA}_{oc,t}^\kappa + \text{CMA}_{ol,t}^\kappa)^{\frac{1}{\kappa}}$. Taking the log of both sides, we derive:

$$\ln \pi_{ot} = \ln B_{ot} - (1 - \beta)\eta \ln Q_{ot} + \eta \ln W_{ot} - \ln \left(\sum_{o'} B_{o't} Q_{o't}^{-(1-\beta)\eta} W_{o't}^\eta \right) \quad (19)$$

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

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

where we set $1 - \beta = 0.25$ following [Ahlfeldt et al. \(2015\)](#) and γ_t is a time-fixed effect.

Like before, the equation for the residential elasticity includes unobserved amenities/productivity and is derived from equilibrium relationships. We need an instrument for $(\ln W_{o,t} - (1 - \beta) \ln Q_{o,t})$ to identify η , because the unobserved residential amenity is potentially correlated with returns to employment in $W_{o,t}$ and residential floor space in equilibrium. We can use the same shift-share instrument we used in the previous section for estimating κ . As such, our LATE in equation 19 will reflect shifts along the residential demand curve correlated with exogenous changes in wages and exclude variation from residential amenities.

We use the shift-share methods in [Borusyak et al. \(2022\)](#), and our estimate is $\hat{\eta} = 1.661$ from Table 2. This is similar in magnitude to the low and high skill residential choice elasticities 2.959 and 3.329 [Tsivanidis \(2023\)](#) finds for Bogotá. A lower estimate reflects less movement across neighborhoods, and a lower elasticity for Medellín relative to Bogotá is potentially consistent with Bogotá being a larger, more international city.

6.3 Crime Externality and Amenities, and the Extradition of Gang Lords

Criminal 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, we derive the following structural relationship linking wages w_d ,

the productivity residual $a_{d,t}$, land/factor prices $q_{d,t}$, and the crime externality $\Upsilon_{dc,t} = \frac{H_{Edc,t}}{K_d}$:

$$w_{d\ell,t} = \alpha(1 - \alpha)^{\frac{1-\alpha}{\alpha}} a_{d,t}^{\frac{1}{\alpha}} q_{d,t}^{\frac{\alpha-1}{\alpha}} \Upsilon_{dc,t}^{\frac{\lambda}{\alpha}}$$

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

$$\Delta \log \left(\frac{a_{d,t}}{\bar{a}_t} \right) = (\alpha - 1) \Delta \log \left(\frac{q_{d,t}}{\bar{q}_t} \right) - \alpha \Delta \log \left(\frac{w_{d,t}}{\bar{w}_{d\ell,t}} \right) - \lambda \Delta \log \left(\frac{\Upsilon_{dc,t}}{\bar{\Upsilon}_t} \right), \quad (20)$$

where $\bar{a}_t, \bar{q}_t, \bar{a}_t, \bar{\Upsilon}_t$ are geometric means defined as $\bar{x}_t = \exp(\frac{1}{S} \sum_{d=1}^S \log(x_{dt}))$ and Δ differences out time-invariant aspects of productivity, so that equation 20 has mean 0. We then arrive at the following moment condition:

$$\mathbb{E} \left[h(Z) \Delta \log \left(\frac{a_{dt}}{\bar{a}_t} \right) \right] = 0, \quad (21)$$

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

Criminal Residential Amenity Our moments for estimating the effect of crime on residential amenities come from the sector choice probability equation:

$$\pi_{ost|om,t} = \frac{L_{os,t}}{L_{o,t}} = \frac{B_{os,t} W_{ost|o,t}^\kappa}{B_{oc,t} W_{oct|o,t}^\kappa + B_{ol,t} W_{olt|o,t}^\kappa} \quad (22)$$

Using equation 22 and taking the ratio for $s = \ell$ to $s = c$, we get:

$$\frac{L_{ol,t}}{L_{oc,t}} = \frac{B_{of,t} W_{olt|o,t}^\kappa}{B_{oc,t} W_{oct|o,t}^\kappa} = b_{o,t} \Upsilon_{o,t}^\omega \frac{W_{olt|o,t}^\kappa}{W_{oct|o,t}^\kappa}, \quad (23)$$

where: $\frac{B_{ol,t}}{B_{oc,t}} = b_{ol,t} \Upsilon_{o,t}^\omega$. Similar to how we derived moment conditions for the productivity externality, we take the difference across periods and divide by the geometric means to get (Ahlfeldt et al., 2015):

$$\Delta \ln \left(\frac{b_{o,t}}{\bar{b}_{o,t}} \right) = \Delta \ln \left(\frac{L_{ol,t}}{\bar{L}_{ol,t}} \right) - \Delta \ln \left(\frac{L_{oc,t}}{\bar{L}_{oc,t}} \right) - \omega \Delta \ln \left(\frac{\Upsilon_{o,t}}{\bar{\Upsilon}_{o,t}} \right) - \kappa \Delta \ln \left(\frac{W_{ol|o,t}}{\bar{W}_{ol|o,t}} \right) + \kappa \Delta \ln \left(\frac{W_{oc|o,t}}{\bar{W}_{oc|o,t}} \right) \quad (24)$$

This implies the following structural moment condition for each sector:

$$\mathbb{E} \left[h(Z) \Delta \log \left(\frac{b_{os,t}}{\bar{b}_{os,t}} \right) \right] = 0 \quad (25)$$

Identification As with our elasticity parameters, unobservables and simultaneity pose challenges to identifying our externality parameters.

To isolate the impact of crime on firm productivity λ and amenities ω , we require a quasi-experimental change in local crime rates. We derive variation in crime through turf wars that resulted as a consequence of the extradition of drug lords. In Medellín, street gangs are under the hierarchy of larger gang leaders. When gang lords are no longer in control of neighborhoods, other gangs fight for the turf, leading to a substantial increase in local crime rates. One such example was related to the extradition of Don Berna, one of the largest gang lords in Medellín, during the early 2000s. When Don Berna was extradited to the US in May 2008, a turf war ensued on his territory. Figure B.3 shows a spike in homicides in formerly-Don Berna neighborhoods, relative to all other neighborhoods in the city. The raw trends in the pre-extradition period show almost identical levels and parallel trends in homicides. This relative increase in homicides was accompanied by increases in other types of crime, such as property crime and extortion; all of which may affect the ability of firms and businesses to function properly, and the amenity value to residents (Rozo, 2018; Sviatschi, 2022).

In Figure B.4 we show that property rental rates and wages earned fell differentially in Don Berna neighborhoods, reflecting the substantial negative impacts of this increase in crime rates. These impacts were concentrated in Don Berna neighborhoods, and we use the corresponding reductions in firm productivity and amenities to identify λ and ω . As in Ahlfeldt et al. (2015), we are able to separately identify the externalities of crime on firm productivity and amenities because our model provides a separate equilibrium condition for each. In particular, our model specifies optimal firm production, which helps us identify productivity changes, and optimal residential choices, which identifies amenity changes.

We want to identify λ and ω using variation derived from these crime externalities rather than other drivers of $\Delta \log\left(\frac{a_{dt}}{a_t}\right)$ (e.g., changes in the distribution of productivity due to a change in zoning laws) and $\Delta \log\left(\frac{b_{ot}}{b_t}\right)$, respectively. Our Don Berna instrument captures only variation in local exposure to crime productivity and residential amenity externalities. We construct instruments $h(Z)$ based on how far neighborhoods were from locations affected by the gang areas of a local crime lord (i.e., Don Berna). The extradition led to a relatively meaningful increase in crime rates in the neighborhoods that were under Berna’s control. We leverage the extradition as a source of exogenous variation in criminal activity to identify the effects of increased crime on economic activity and residential amenities. Variation across different bands of distances from Don Berna neighborhoods helps identify λ by highlighting differences in homicide increases created by variation in exposure to the Don Berna extradition.

We implement estimation of the crime productivity externality parameter using GMM and find $\hat{\lambda} = -0.062$ (Table 2, column 3). Given the unique nature of our crime data, we lack close analogs in the literature. Potential points of comparison are the production agglomeration parameters Tsivanidis (2023) and Ahlfeldt et al. (2015) estimate of 0.212 for Bogotá and 0.07 for Berlin, respectively. While these parameters capture different economic forces (i.e., positive

rather than negative externalities), they also originate from specifications based off of [Ahlfeldt et al. \(2015\)](#) and reflect reasonable magnitudes for externality parameters in this class of models.

For the crime-amenity effect, we estimate $\hat{\omega} = -0.146$ in Table 2, column 4. We also lack a close comparison for our criminal residential amenity parameter in the literature. We use [Tsivanidis \(2023\)](#)'s neighborhood agglomeration parameters for high and low-skill workers of 0.414 and 0.576 as benchmarks for reasonable residential amenity parameter magnitudes for these types of models.

6.4 The Returns to Crime

The share of criminals living in origin o choosing to commit a crime in destination d is:

$$\pi_{odct|oc,t} = \frac{w_{dc,t}^{\theta_c} \tau_{od,t}^{-\theta_c}}{\sum_{d'} (w_{d'c,t} / \tau_{od',t})^{\theta_c}}$$

Substituting in our equation 10 for the returns to crime and taking logs:

$$\log(\pi_{odct|oc,t}) = \theta_c \log(A_{dc,t}) + \rho \theta_c \log(H_{dc,t}) + \iota \theta_c \log(H_{dl,t}) - \theta_c \tau_{od,t} - \log\left(\sum_{d'} (w_{d'c,t} / \tau_{od',t})^{\theta_c}\right),$$

where $\tilde{A}_{dc,t} = (1 - p_{d,t}) A_{dc,t}$. Redefining $\tilde{A}_{dc,t}$ as part of an error term $\epsilon_{od,t}$, this can be translated into the following estimation equation:

$$\log(\pi_{odct|oc,t}) + \log\left(\sum_{d'} (w_{d'c,t} / \tau_{od',t})^{\theta_c}\right) = \rho \theta_c \log(H_{dc,t}) + \iota \theta_c \log(H_{dl,t}) - \theta_c \tau_{od,t} - \gamma_o + \epsilon_{od,t} \quad (26)$$

This depends only on observables $(\pi_{odct|oc,t}, H_{dc,t}, H_{dl,t}, w_{dl,t}, \tau_{od,t})$ and separately estimated parameter θ_c .

Similarly to the productivity and amenity externalities, several unobservables could cause the total number of criminals in a given destination $H_{dc,t}$ to covary with the share of criminals and legitimate sector workers commuting from origin o to destination d . For example, in the case of criminals, d could be the headquarters for a gang with a strong presence in o in period t . We have assumed that crime affects productivity and vice versa, so there is a simultaneity problem when estimating ρ and ι . As such, we use the Don Berna instrument to identify ρ as it captures exogenous variation in criminality; and use the previously-discussed shift-share Bartik shocks to identify ι as they generate exogenous variation in legitimate sector workers.

Under this setup, we control for unobserved criminal productivity $\tilde{A}_{dc,t}$ using fixed effects. We find $\hat{\rho} = -0.277$ and $\hat{\iota} = 0.146$ (Table 2, column 5).

6.5 Other Parameters

We take some parameters from the literature. Specifically, $(1 - \beta)$, $(1 - \mu)$, $(1 - \alpha)$, which are, respectively, the share of residential floor space in consumer expenditure, the share of land in construction costs, and the share of commercial floor space in firm costs. These are set following Ahlfeldt et al. (2015) to $\alpha = 0.8$, $\mu = 0.75$, $\beta = 0.75$. For the time disutility parameter δ , as mentioned above, we follow the growing consensus in the literature (Ahlfeldt et al., 2015; Tsivanidis, 2023; Zárate, 2022) and set it to $\delta = 0.01$.

6.6 Model Inversion

Given the value of the parameters, we can recover the fundamentals of the model $\{B_{os}, A_d\}$.²⁴ In order to do so, we first solve for commuter and firm market access given observed residential and labor decisions through equations 32 and 33. Given the recovered $\{CMA_o, FMA_o\}$, one can obtain the model-implied wages from the sectoral labor supply equation:

$$H_{ds} = w_{ds}^\theta FMA_{ds}$$

Given the recovered distribution of wages in the legitimate and in the criminal sector, we recover productivity in the legitimate sector using the production function and profit maximization:

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

Finally, $\{B_{os}\}$ are shifters that attract workers from particular sectors to certain neighborhoods of residence. In order to see this, note that the ratio of the share of individuals from a particular origin that chooses to work in the legitimate sector relative to the criminal sector is given by:

$$\frac{\pi_{ol|o}}{\pi_{oc|o}} = \frac{B_{ol}}{B_{oc}} \left[\frac{CMA_{ol}^{1/\theta_\ell}}{CMA_{oc}^{1/\theta_c}} \right]^\kappa$$

Thus, we can recover the relative amenities B_{ol}/B_{oc} by fitting the number of legitimate workers relative to criminals given observed sectoral commuter market access.

7 Policy Counterfactuals

What are the sectoral choice effects of transportation infrastructure investments? Does connecting poor neighborhoods to the Central Business District (CBD) import opportunity or export crime? Which neighborhoods should we target for transit expansions? What are the resulting welfare effects? We first answer these questions through the lens of the model focusing on two network-based counterfactuals motivated by public policy. We then conduct a different exercise, where we try to unpack which neighborhoods should be the targets of transportation improvements, by reducing the average commute time at each origin neighborhood, and examining the welfare and criminality consequences of such an intervention.

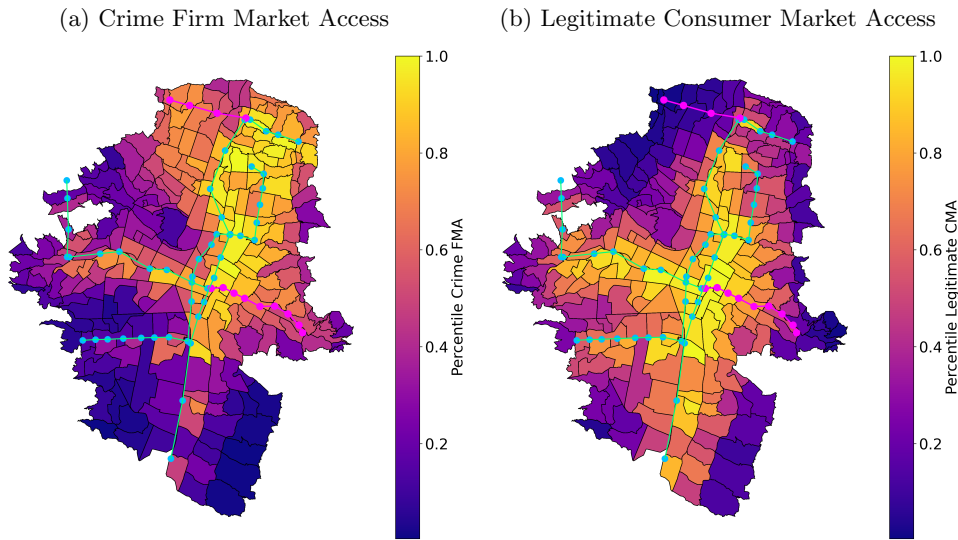
²⁴For this version of the results, we assume that $B_o = 1 \quad \forall o$, and that $\xi_d = 1 \forall d$.

7.1 Equilibrium Effects of Recent Network Lines

We examine the dynamics surrounding crime rates and city-level welfare, when we build new network-based public transport lines. We discipline our analysis by focusing on the lines that were recently built, and were not a part of our estimation sample. First, we evaluate the impacts of a new cable line that was opened in mid-2021, in the north-western part of the city. We then evaluate the consequences of a tram line built in 2016 by the government in Medellin that connected the eastern part of the city to the CBD.

These two lines provide interesting nuances, given the baseline market access and composition of the neighborhoods. The eastern edge of the city has high baseline crime activity, but also easy access to legitimate sector firms via a dense pre-existing bus network. The north-western part has even higher crime rates, but lower legitimate-sector consumer market access as there existed little public transportation at baseline connecting these neighborhoods to profitable legitimate employment opportunities. The differences in the outcomes describe how baseline characteristics affect the equilibrium outcomes for both criminality and welfare.

Figure 6: Sectoral Market Access, 2015



Notes: These maps show the percentiles of recovered Firm Market Access for crime on panel a) and Consumer Market Access for legitimate-sector work in panel b). Both variables are measured in 2015.

Importantly, the newly connected neighborhoods under both counterfactuals were relatively poor neighborhoods where criminals tended to live. Figure 6 shows the percentiles of Firm Market Access for crime and Consumer Market Access for legitimate work in 2015. Firm Market Access for crime measures how many residents of different neighborhoods tend to work in crime, while Consumer Market Access for legitimate work measures how close these neighborhoods are to profitable legitimate employment opportunities. The map shows a stark contrast between these variables in both the north-western and eastern parts of the city. Specifically, crime FMA is large relative to legitimate-sector CMA: individuals living in these neighborhoods

tended to choose the criminal sector instead of the legitimate sector in 2015.

Ex-ante, the effect of connecting these neighborhoods to the CBD on individuals' sector choice is ambiguous. On the one hand, reducing commute costs to the CBD increases legitimate-sector CMA for connected neighborhoods since they will now be able to commute to neighborhoods with large returns for legitimate-sector work. On the other hand, reducing commute costs also increases criminal CMA since, in principle, criminals are connected to more profitable crime destinations near the CBD. The overall effects will depend on the change in relative sectoral CMA, which, in turn, will depend on the estimated parameters.

In order to understand the counterfactual effects of the tram line on sector choice and welfare, we proceed as follows: we invert the model to obtain unobserved amenities and productivities consistent with the data in 2015. Then, given the estimated parameters, we feed the model with the observed change in commuting costs as a result of the new lines and solve for the endogenous variables.²⁵ We then analyze the economy's response to the commute cost shock.

7.1.1 The North-West Cable Line

We first study the sector choice and welfare impacts of a cable line that the government actually implemented after our data sample. The government of Medellín constructed a new cable line that connects the northwestern part of the city to the rest of the transportation network. This line started operating in June, 2021.

Based on Figure 6, we know that the north-western part of Medellín is a high-crime Firm Market Access region, which reveals that criminals tend to live in these neighborhoods. In order to evaluate the welfare effects of the cable line, we construct counterfactual commute times considering the new public transport stations. We invert the model and obtain unobserved fundamentals in 2015 consistent with the data. We then feed the model with the counterfactual change in commute times and study the resulting equilibrium.

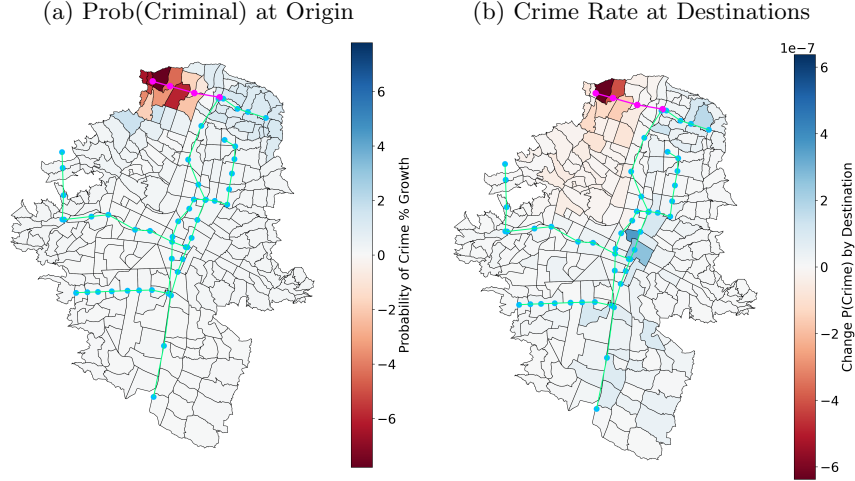
Figure 7 shows the main results of this exercise. The map plots the percent change in the probability of becoming a criminal for each neighborhood in Medellín. According to the model, the new cable line reduced the probability of becoming a criminal in treated neighbors by as much as 1.77%. For the neighborhoods that saw at least a reduction of 10 mins in average commute times, crime participation rates fell by 6.14% on average. The percent decrease in the probability of becoming a criminal is larger for more remote neighborhoods: it is these neighborhoods that benefit the most from being connected to the transportation network, given that they previously did not have access to profitable legitimate-sector work opportunities.

So far, we show that with the extensive margin of sector choice, we find an 'importing opportunity' reduced criminal participation. We now explore the intensive margin of crime by focusing on the destination decisions conditional on sector and origin. The right panel of Figure 7 shows an 'exporting of crime', by documenting the change in the probability of committing a crime by destination conditional on becoming a criminal.

²⁵In the presence of externalities, there is potential for multiple equilibria. Following Ahlfeldt et al. (2015), we assume that the equilibrium selection rule is the closest to the equilibrium observed in the data before the shock.

Conditional on having chosen to become a criminal, the decline in commute times allows individuals to commit crimes in more profitable destinations (e.g., near downtown). In this sense, criminals substitute away from local crime and start committing crimes in neighborhoods with high model-implied returns to crime, particularly in the CBD.

Figure 7: Change in crime rate: North-west Cable line



Notes: Left-panel map shows the model implied percent change in the probability of becoming a criminal conditional on origin, $\pi_{oc|o}$ across neighborhoods of origin, given the change in commute costs. Right-panel map shows the model implied percent change in the probability of committing a crime conditional on origin, $\pi_{od|o}$ across neighborhoods of destination, given the change in commute costs.

Finally, we study the welfare effects of this particular investment in transportation. We assume that the total population of Medellín does not change after the reduction in commute times, and compute the change in expected utility after the shock. That is, we evaluate the change in expected welfare due to the construction of the new cable line, assuming that there is no in nor out-migration from Medellín. Consistent with the results found so far, the model predicts a positive welfare impact on the average city resident of 0.42%, and a GDP increase of \$2 billion USD (net of costs).²⁶

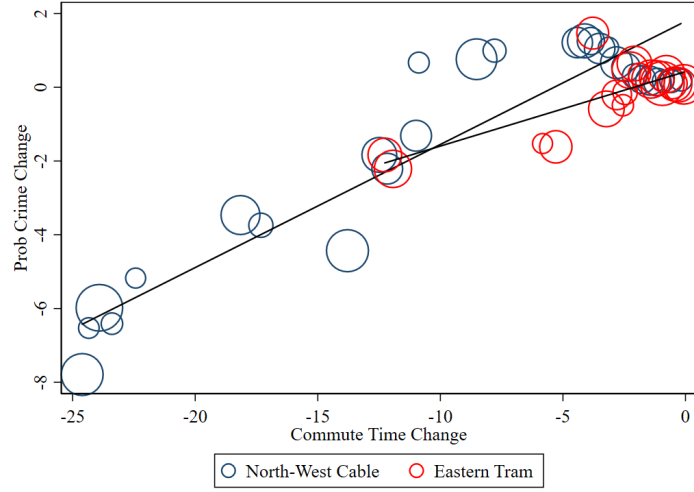
7.1.2 The Eastern Tram Line

The meaningful impacts in the northwest were partly driven by a lack of pre-existing public transportation infrastructure in that part of the city. In comparison, we examine the effect of a tram line that connected parts of the city that already had an existing bus network. In 2016 the government of Medellín invested in a tram line that connected neighborhoods in the eastern part of Medellín to the CBD.

According to our estimates, the tram increased legitimate-sector CMA relative to criminal CMA in treated neighborhoods, therefore reducing the probability of becoming a criminal by

²⁶GDP is the sum of factor payments to legitimate factors (i.e., legitimate-sector earnings and housing rents). We discount GDP by 10% over a 50-year period. The costs for the cable are paid upfront (not discounted). The costs are the documented costs in the official budgets after the cable is functional.

Figure 8: Relationship Between Change in Commute Cost and Sector Choice



Notes : The scatterplot shows the relationship between the percent change in average commute costs at the origin level and the percent change in the probability of becoming a criminal at the origin level as well by counterfactual. We binned the changes using equal distance.

up to 2%. Yet, there were also neighborhoods with increased criminal participation, as we now connected certain low-crime low-income neighborhoods along the route, to more high-criminal opportunity neighborhoods at the extreme eastern edge of the city.²⁷

The eastern tram line was built in 2015, and so for this counterfactual, we can use data from subsequent years to test how well our model predicts key economic outcomes in the actual data. We present these results in Figure B.6. While there were numerous other (unmodeled) concurrent changes occurring in the economy over that period, our model does a reasonable job of predicting changes in crime rates, and wages and rents.

Why was the overall impact on crime rates smaller under this tram line than under the north-west cable line? In order to see this more clearly, Figure 8 shows the relationship between the decline in average commute costs and the change in the probability of becoming a criminal by origin for each line. The relationship is somewhat non-linear, but shows larger reductions in criminal participation for neighborhoods with larger declines in average commute costs. Importantly, compared to the north-west cable counterfactual considered in Section 7.1.1, the investment in the new cable line had a smaller and more geographically concentrated impact on the probability of becoming a criminal. That is, the figure also shows that the reductions in commute costs for the north-west cable were far larger than that for the eastern tram line, as the east already had a meaningful pre-existing bus network. Given the pre-existing bus network, the overall change in legitimate-sector CMA for the eastern neighborhoods was not as large.

Performing the welfare exercise, we find that building the tram increased expected utility in the city by a much smaller 0.09%. The smaller welfare impact is due, on the one hand,

²⁷Similar to the last counterfactual, when studying criminal destination decisions, we find that criminals substitute local for distant crime by changing the location of their crimes towards the CBD.

mechanically to the smaller decline in overall commute costs in the city. More importantly, it is due to the fact that there is a smaller reduction in the negative externalities imposed by crime precisely because the new line connected relatively well-connected neighborhoods, thus not having as large of an impact on the number of criminals in the city.

7.2 Which Neighborhoods Should Be Targeted?

The consequences described above tell us about recent policy-driven expansions to the transit sector, and the heterogeneity in the impacts suggests that it may be more important to connect certain neighborhoods than others. Which targeted neighborhoods are likely to produce the best city-level outcomes? To answer this question, we reduce the average commute times in each origin o neighborhood by 10 percent. That is, for each o , we set $\tau'_{od} = 0.9\tau_{od} \forall d$. This is similar to a policy where we subsidize ride-sharing facilities or taxis, or give cars to residents of the targeted neighborhoods. Yet, reductions in commuting costs for residents in a neighborhood will affect all other neighborhoods as well, as it changes criminality and legitimate-sector activity not just in the intervention neighborhood, but also crime and work destinations in other parts of the city. To examine the overall consequences, we create city-level resident-weighted averages as outcomes. We focus on outcomes in relation to the baseline access to legitimate-sector opportunities.

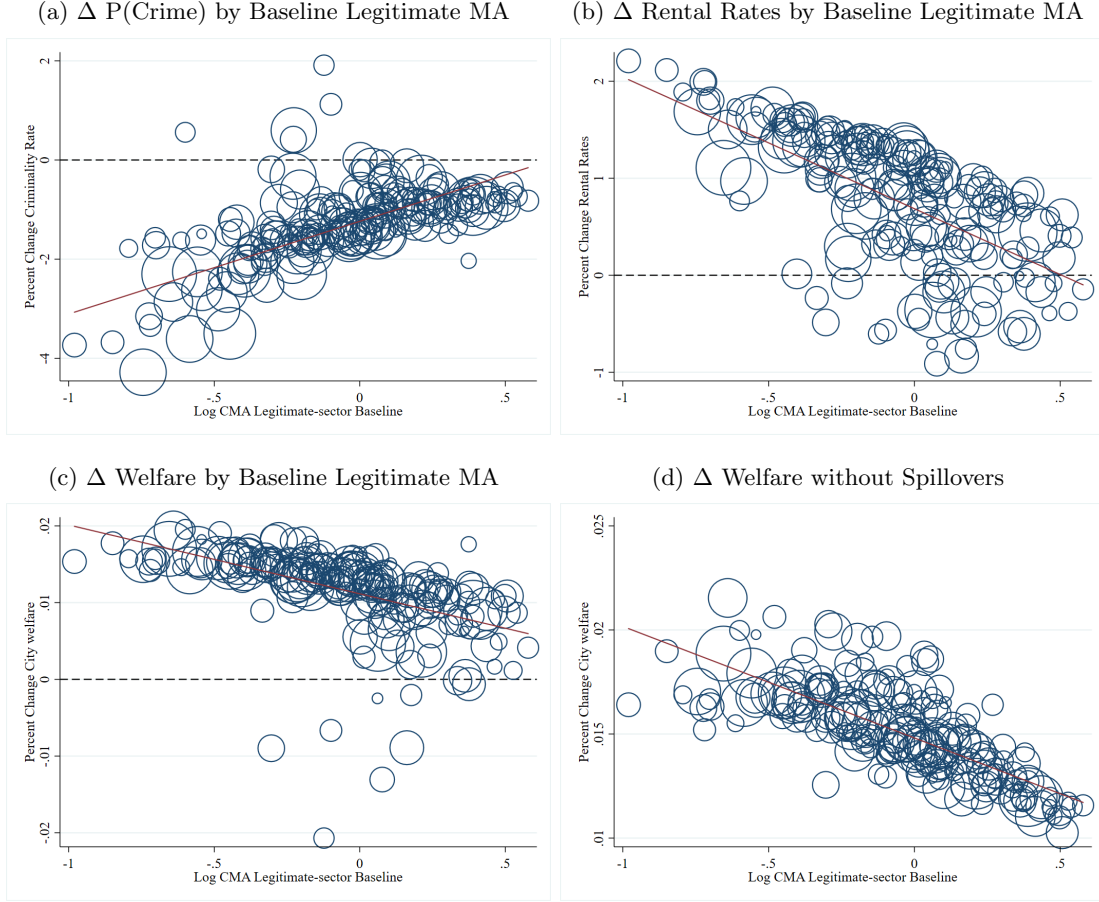
Figure 9 has a clear message: connecting neighborhoods that have the lowest legitimate-sector CMA at baseline is likely to lead to the largest reductions in city-level criminality, and the largest increases in rental prices. The top left panel shows that treating almost all neighborhoods in the city would lead to reductions in city-level crime. Yet, there are a handful of neighborhoods, which, when treated with reductions in commute costs, display increases in city-level crime. These neighborhoods already have high legitimate-sector productivity, and so any transportation improvements there may simply allow residents to access criminal activity elsewhere in the city. These handful of neighborhoods are where there was already high legitimate-sector productivity.

The top right-side panel shows that rental prices increase when residents of most neighborhoods see a reduction in commute costs. This partly reflects the amenity and productivity boosts that emerge out of lower crime, but also the ability to access distant legitimate markets with the help of lower commute costs. Figure 9c shows the welfare consequences of these reductions in transport costs. Across almost any treated neighborhood, there is an increase in city-level welfare, and this increase is slightly higher when areas that have less access to legitimate sector opportunities are treated (left panel). Yet, there are seven neighborhoods (3% of all neighborhoods) that, when treated with reductions in transportation costs, lower aggregate city welfare.

7.2.1 Cross-Sectoral Spillovers and Non-linear Responses

One obvious question is why are there seven neighborhoods where reductions in commute times actually lower welfare across the city? In a study that neglects crime, reducing commuting costs, should always be welfare improving. Yet, since the spread of crime can adversely affect legitimate-sector productivity, lowering commute costs in some neighborhoods may have an

Figure 9: Reducing Commute Costs by Each Neighborhood



Notes: Scatter plots show the relationship between changes in city-level 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. The outcome in the Panel a is the city-level criminality (i.e., $\sum_o P(\text{crime}|\text{origin})x\text{Population}_o$). Similarly, the outcome in the Panel b is the city-level rental rates. Scatter plots in Panel c and d show the relationship between changes in city-level welfare against the baseline legitimate-sector market access for the treated origin o . Panel c shows the effects from the baseline model with high cross-sectoral spillovers. Panel d shows an exercise with no spillovers.

adverse effect. Indeed, our investigation of possible channels suggests that the fall in welfare is mostly driven by the size of the cross-sectoral spillovers we have in our model as shown in our equation 14 welfare decomposition (i.e., how crime lowers legitimate-sector productivity and amenities, and how less legitimate-sector opportunities lower returns to crime). To investigate the importance of these spillovers, we perform the same set of counterfactuals where we simply reduce the magnitude of the spillover parameter from $|\lambda| = 0.062$ to $|\lambda| = 0$.

In Figure 9d we show the results of the counterfactuals, without productivity spillovers, where we subsidize transportation by 10% neighborhood-by-neighborhood, as we did for Figure 9c. Rather interestingly, we see that in a world with no spillovers, all neighborhoods see a substantial improvement in welfare. Yet, under our set of estimated parameters (with spillovers), there are seven neighborhoods that, when connected, raise the aggregate amount of criminal

activity in the city. Since an aggregate increase in criminal activity lowers legitimate-sector productivity (especially when the spillover parameter is large), this lowers overall legitimate-sector wages, and welfare in the city. These dynamics highlight the importance of modeling cross-sectoral spillovers in standard frameworks used in Urban Economics. Ignoring such spillovers may produce a different set of qualitative and quantitative results.

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. Our simulations 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, aggregate crime, welfare, and inequality can all be improved by improving the connectedness of almost any neighborhood.

Yet, 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 distributional gains may then determine whether or not transportation infrastructure is expanded, as increases in crime rates in certain 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 overestimate the effects of reducing commute costs in some

neighborhoods. If we were to ignore cross-sectoral externalities, reducing commute costs will always be welfare-enhancing; yet, accounting for negative externalities driven by crime implies that reducing commute costs can, in certain cases, actually be welfare-reducing as individuals might find it profitable to switch to the criminal sector, hence leading to an overall increase in crime within the city.

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 is not necessarily beneficial to reduce transit costs in all neighborhoods. Yet, even in an extremely high-crime 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.

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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 2009. 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 that participate 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 to make the monthly Social Security payment of workers. In most cases, this payment is made by the companies. We have access to the anonymized information of workers between 2008 to 2018. This database contains monthly level information of wage, 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 Medellín. The entity that registers the firms in Medellín is the *Camara de Comercio de Medellin*. We have 80,268 firms on average by year between 2007 to 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) with the anonymized identification of firms in PILA. This allows us to capture 33,312 firms in 8 years, representing 81% of formal workers in Medellín.

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, neighborhood where the crime took place, date of arrest, criminal group (or gang) the individual belongs to, and 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.2 Rescaling data with Informal sector

We need data on $\{H_{Eds}, H_{Ros}\}$ for $s \in \{c, \ell\}$ and $o, d \in \{1, \dots, D\}$, which is the number of employees by sector-neighborhood and number of residents by sector-neighborhood. Here we explain how we construct these quantities.

A.2.1 Scaling SISBEN resident counts to census resident counts, s_o

The SISBEN surveys a fraction of the whole population in a neighborhood. Specifically, SISBEN only surveys a share, call it s_o , of the total residents in that neighborhood. This is, if H_{Ro} is the true number of residents in neighborhood o , we observe:

$$\tilde{H}_{Ro} = s_o H_{Ro}$$

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

A.2.2 Estimating probability of criminals being arrested by destination, p_d

\tilde{H}_{Edc} is obtained from the arrest data, which tells us the number of arrested criminals by destination. The number of arrested criminals in neighborhood d is not necessarily the same as the total number of criminals that commits crimes in that neighborhood $\tilde{H}_{Edc} \neq H_{Edc}$ because we observe captured criminals instead of total crimes happening at a destination. Theoretically:

$$\tilde{H}_{Edc} = H_{Edc} \times p_d$$

where p_d is the probability of getting caught. Using a proxy for p_d , we can then obtain

$$H_{Edc} = \frac{\tilde{H}_{Edc}}{p_d}$$

We compute p_d as the ratio between captured individuals and crimes committed at neighborhood d from 2003 to 2015. Crimes committed are obtained from the Colombian police records of homicides and property crimes.

A.2.3 Scaling crime to get the total number of criminals by origin, H_{Roc}

\tilde{H}_{Roc} is obtained by matching the arrest data with the SISBEN. In principle, there could also be criminals that are not matched to the Sisben $\tilde{H}_{Roc} \neq H_{Roc}$.

We can decompose the true total of criminal residents in o into those that are matched in the Sisben and others:

$$H_{Roc} = H_{Roc}^{Sisben} + H_{Roc}^{Other}$$

We can reasonably assume that $H_{Roc}^{Other} \approx 0$, because SISBEN captures the 70% poorest households, which are more likely to participate in crime.²⁸

$$H_{Roc} = H_{Roc}^{Sisben}$$

By definition:

$$H_{Roc}^{Sisben} = \sum_d H_{Eodc}^{Sisben}$$

That is, the total number of criminal residents in o is equal to the sum of all criminal commuters across all destinations.

In this sense, we don't observe the true SISBEN flows H_{Eodc}^{Sisben} because some criminals are not captured. We observe a proxy given by those criminals that are captured $\tilde{H}_{Eodc}^{Sisben}$. We assume that the observed flow of captured criminals is equal to the true flow times the probability of being captured in that destination:

$$\tilde{H}_{Eodc}^{Sisben} = H_{Eodc}^{Sisben} p_d ,$$

where p_d is the probability of being captured. We can thus recover true flows as:

$$H_{Eodc}^{Sisben} = \frac{\tilde{H}_{Eodc}^{Sisben}}{p_d}$$

and thus:

$$H_{Roc} = \sum_d \frac{\tilde{H}_{Eodc}^{Sisben}}{p_d}$$

A.2.4 Scaling legitimate workers to get the total number of workers by origin, H_{Rol}

The true number of residents in origin o can be decomposed into the criminal residents of origin o and the legitimate workers in that neighborhood: $H_{Ro} = H_{Roc} + H_{Rol}$. From the discussion above:

$$\tilde{H}_{Ro} = s_o H_{Ro} = s_o (H_{Roc} + H_{Rol}) ,$$

²⁸The richest households are less likely to be involved in crime. The arrest rate for male youth in the middle of the SISBEN distribution (SISBEN score 40-45) is 6.8%. However, the arrest rate for the richest among the low-income SISBEN population (SISBEN score above 75) is only 1.8%.

Also as discussed above we can obtain the number of criminal residents by summing across criminal commuters scaled by the probability of getting captured $H_{Roc} = \sum_d \frac{\tilde{H}_{Edc}^{Sisben}}{p_d}$, and hence obtain the true number of residents of a neighborhood o as:

$$H_{Ro} = \frac{\tilde{H}_{Rol}}{s_o} - H_{Roc}$$

where we are proxying for s_o using the share of the total population in the Census that we capture with our data, so everything on the right-hand side is observed.

A.2.5 Scaling formal or informal workers to get the total number of formal or informal by destination

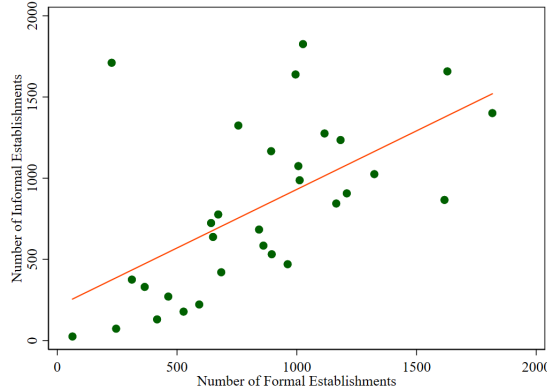
Another challenge with the data is to incorporate informal workers. In this sense, from the SISBEN, we know the share of informal workers by origin, i_o . Then, we compute $H_{Roi} = H_{Rol}i_o$ and $H_{Rof} = H_{Rol}(1 - i_o)$.

Formal worker flows origin-destination, H_{Eodf} , are obtained by matching the PILA data with SISBEN. Then $H_{Edf} = \sum_o H_{Eodf}$.

Informal workers flows origin-destination, H_{Eodi} , are obtained assuming the same share of formal workers flows. Then $H_{Edi} = \sum_o \left(\frac{H_{Eodf}}{H_{Rof}} \right) H_{Roi}$.

Essentially, in our data, we observe: (1) where formal workers live, (2) where formal workers work, and (3) the individual-level flows from where they live to where they work. For informal workers, we only observe (1) and (2), but not (3). Figure A.1 shows that establishments are located in similar destinations. So we assume the probability of flows to a destination, conditional on origin, are the same for formal and informal workers.

Figure A.1: Formal vs Informal Establishment Locations



Notes: Figure shows the number of formal establishments vs the number of informal establishments by neighborhood. Neighborhoods are grouped in bins of 50 establishments. The number of informal establishments is obtained from [Straulino et al. \(2022\)](#).

A.2.6 Adjusting for if 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. Suppose after all the adjustments we find that

$$\sum_o H_{Ros} < \sum_d H_{Eds}$$

We then do the following final adjustment:

$$H'_{Ros} = \left(\frac{\sum_d H_{Eds}}{\sum_o H_{Ros}} \right) H_{Ros} ,$$

which implies $\sum_o H'_{Ros} = \sum_d H_{Eds}$

Similarly, if after all the adjustments, we find that

$$\sum_o H_{Ros} > \sum_d H_{Eds}$$

We then do the following final adjustment:

$$H'_{Rds} = \left(\frac{\sum_o H_{Eos}}{\sum_d H_{Rds}} \right) H_{Rds} ,$$

which implies $\sum_d H'_{Rds} = \sum_o H_{Eos}$

A.3 Constructing Commute Times

In this section, we describe how we compute commute times for the public transport for 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.²⁹ 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 distance of our travel times and Google's times. The parameters of our network can be summarized in the next table.

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

²⁹The 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

Table A.1: Spatial Network Calibration

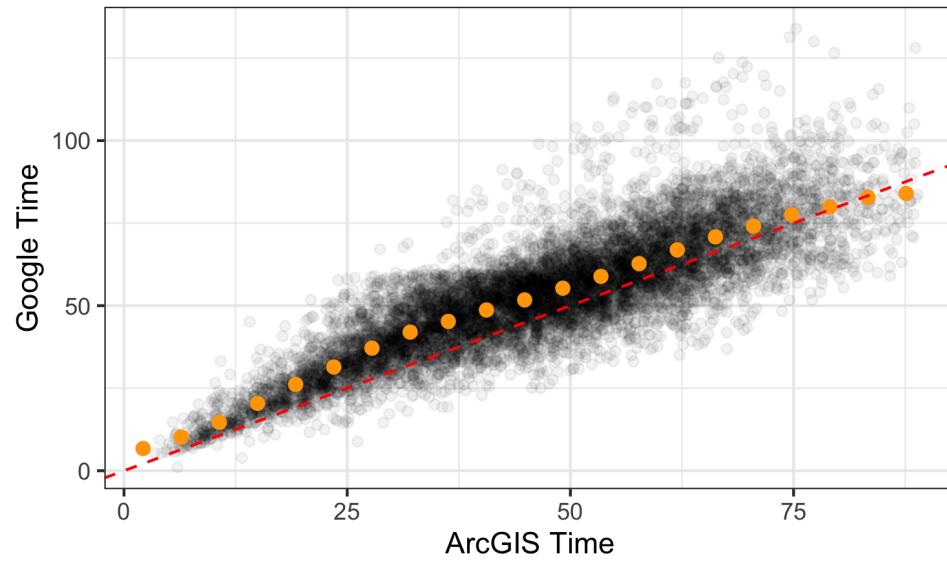
Transport parameters	speed
Train lines	40km/h
Tram	16km/h
Aerial cable	18km/h
Metroplus bus	16km/h
Regular bus	16km/h
Walking speed	5km/h
Train station stop time	15s
Bus station stop time	30s

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

	<i>Dependent variable:</i>
	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)
<i>Note:</i>	*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:

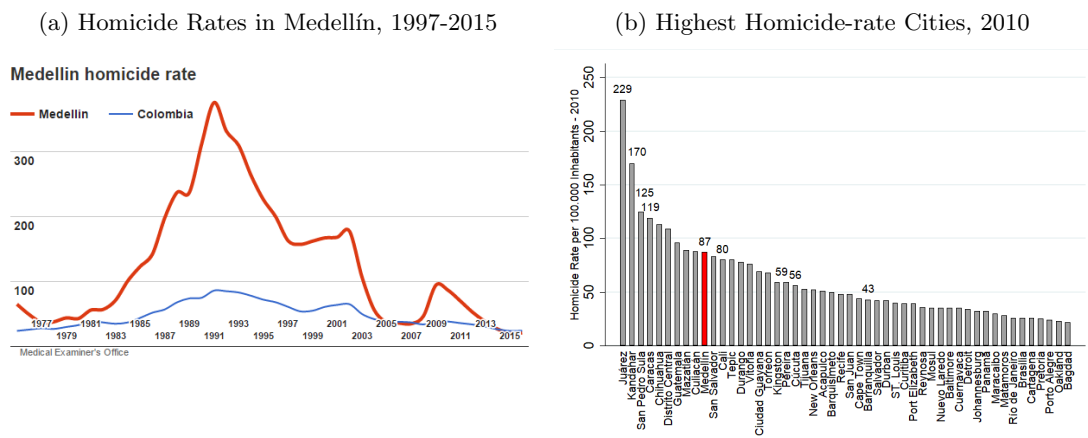
Figure A.2: Comparing Google-based and ArcGIS Commute Times (public transport)



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.

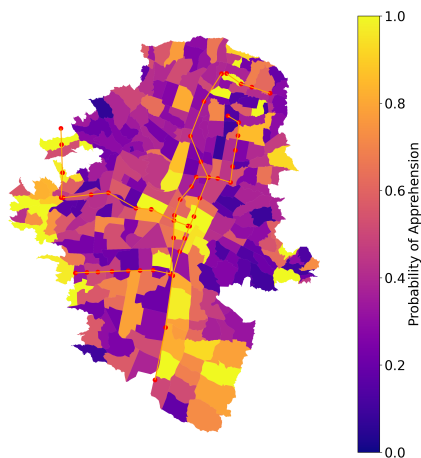
B Appendix: Additional Figures and Tables

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



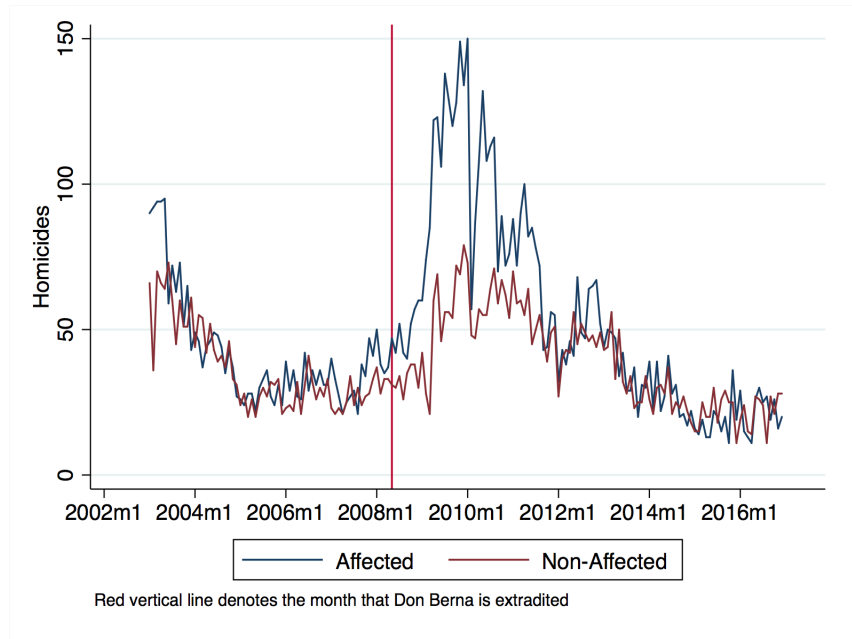
Note: Homicides rates in Medellín over time (left panel), shows the number of recorded homicides per 100,000 individuals in Medellín (red line) and the average for Colombia (blue line). Data from the *Consejo Ciudadano para la Seguridad Publica y la Justicia Penal*. The right panel shows the average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

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



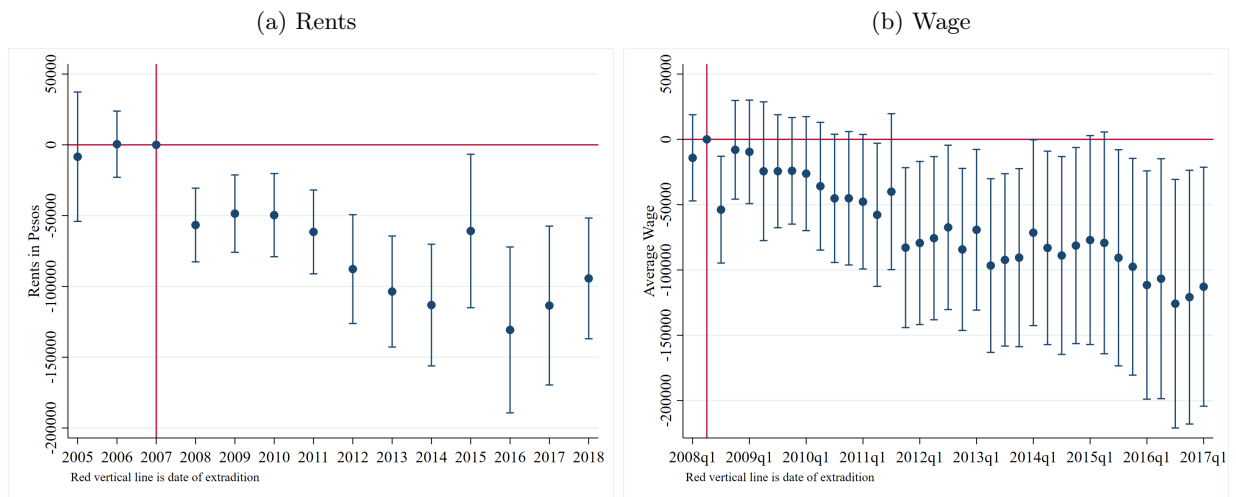
Notes: This map shows the average arrest rate $\#arrests_d / \#homicides_d$ across the sample.

Figure B.3: Change in Homicides After the Extradition of Crime Lord, Don Berna



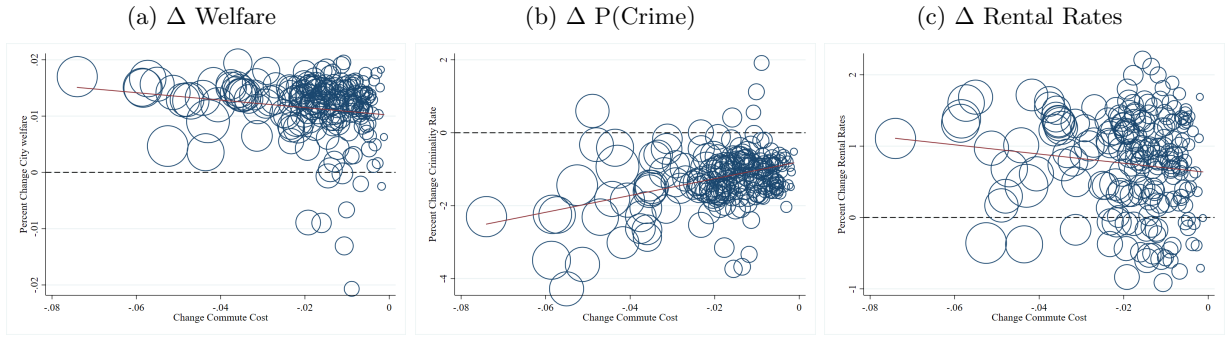
Notes: This map shows the homicide rate by neighborhoods that Don Berna used to be in charge of (affected), and all other neighborhoods (not affected). After his extradition, there was a spike in crime in his neighborhoods.

Figure B.4: Effect of Don Berna Shock



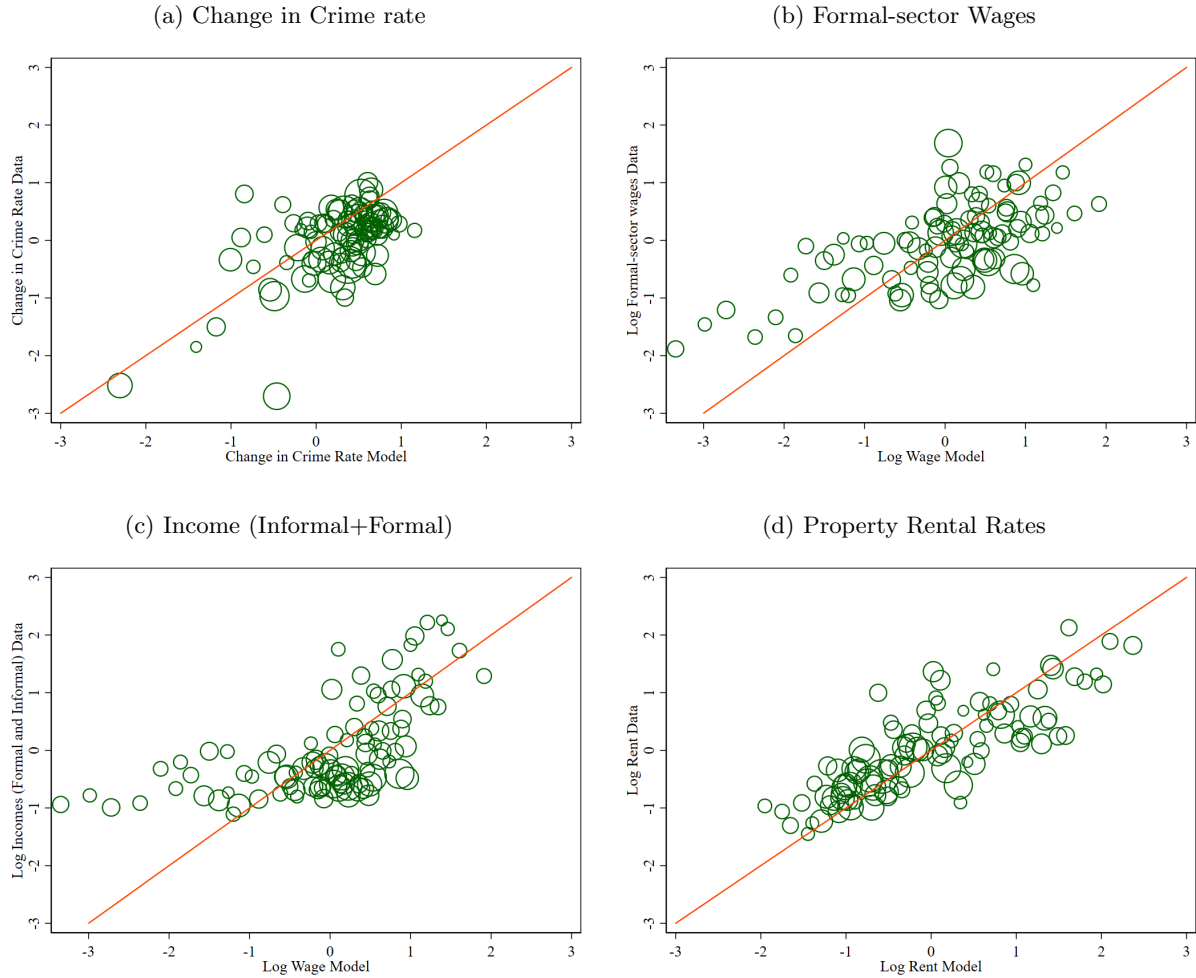
Notes: Figures show the effect of Don Berna extradition on those neighborhoods that Don Berna used to be in charge of. The left panel shows property rental rates. The right panel shows quarterly wages for formal sector workers.

Figure B.5: Reducing Commute Costs by Each Neighborhood: Robustness



Notes: Scatter plots show the relationship between changes in city-level welfare, criminality and rental rates against the absolute change in commute times for the treated origin o , where treatment is a ten percent reduction in commute costs ($\tau'_{od} = 0.9\tau_{od} \forall d$).

Figure B.6: Data validation of the model using tram line counterfactual



Notes: Scatter plots show the correlation between the model prediction on the Change in Crime Rates, Wages, and Rents with actual data. We introduce in the model the new commute times after the opening of the tram line in 2015, and solve it to obtain the Crime Rates, Wages, and Rents values for each neighborhood. As sources for the actual data, we use the Police records for 2015 to 2016, the Encuesta de Calidad de Vida (ECV) for the household income in 2016 and the rents in 2017, and the PILA for the formal-sector wages in 2017. Panel a shows the correlation between the predicted change in crime rate for the model and the actual change in 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 predicted wage for the model 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 by each bin.

Table B.1: 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*** (0.0034)	-0.0674*** (0.00345)	-0.0644*** (0.0064)	-0.0641*** (0.00642)	-0.0386*** (0.0078)	-0.0382*** (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	1,157,776	1,157,776	1,157,776	1,157,776	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 1. 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 with gang. We thank Arantxa Rodriguez-Urbe for sharing data on gang boundaries.

Table B.2: Commuting Elasticity by Type of Crime

	Any crimes	Violent Crime	Property	Drugs	LACE Crimes
Minutes from O-D	-0.0676*** (0.0034)	-0.0644*** (0.0064)	-0.0645*** (0.0052)	-0.0682*** (0.0036)	-0.0675*** (0.0062)
Observations	1,157,776	1,157,776	1,157,776	1,157,776	1,157,776
Destination-by-Time FE	Yes	Yes	Yes	Yes	Yes
Origin-by-Time FE	Yes	Yes	Yes	Yes	Yes
Destination-by-Origin FE	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”. 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 B.3: Effect of a New Station on the Probability of Arrest

	Probability of Arrest		
	Property-Homicides	Homicides	Property
Log(Distance to Station)*Post	0.0363 (0.0320)	-0.00347 (0.0351)	0.108 (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 of property and homicide crimes. Column 2 and 3 show the effect on the probability of arrest of homicides and property crimes, respectively.

C Additional Reduced-form Relationships

Table C.1: The Effects of New Cable Lines on Crime

	Any Crime	Violent Crime	Any Crime	Violent Crime
Panel A: Effects on Destination (Crime Locations)				
Log(Distance to Station)xPost	0.0970** (0.0438)	0.180*** (0.0523)	0.115** (0.0464)	0.218*** (0.0566)
Observations	3,766	3,766	1,013,054	1,013,054
Data Structure	Destination-by-time		Origin-by-Destination-by-time	
Destination Fixed Effects	Yes	Yes	Yes	Yes
Origin Fixed Effects	No	No	Yes	Yes
Origin-Destination Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
SE Cluster	Destination	Destination	Two Way: Origin-Dest	
Panel B: Effects on Origins (Criminal Participation)				
Log(Distance to Station)xPost	0.0693*** (0.0232)	0.154*** (0.0316)	0.0724** (0.0294)	0.163*** (0.0366)
Observations	3,766	3,766	1,013,054	1,013,054
Data Structure	Origin-by-time		Origin-by-Destination-by-time	
Destination Fixed Effects	No	No	Yes	Yes
Origin Fixed Effects	Yes	Yes	Yes	Yes
Origin-Destination Fixed Effects	No	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
SE Cluster	Origin	Origin	Two Way: Origin-Dest	

Notes: The first two columns of Panel A show difference-in-differences estimates for being close to a station, and crime destinations. The first two columns of Panel B show the effects on origins (residences) of crime perpetrators. The data in the first two columns of Panel A are shaped to be at the time by destination-of-crime level. The data in the first two columns of Panel B are at the time by origin-of-crime level. Both sets of regressions suggest that crime falls in areas closer to newly built stations. The last two columns of Panel A show difference-in-differences estimates for being close to a station, and crime destinations. The last two columns in Panel B show the effects on origins (residences) of crime perpetrators. The data in the last two columns are at the origin-by-destination-by-year level.

C.1 Travel Time and Net Effects Across Lines

The time to a cable station $Minutes\ to\ Station_{ot}$ changes as and when new stations and lines are built. Such a method conveniently allows us to summarize the consequences of simultaneous different changes to parts of the transit network, and leverage information on actual travel times, which more closely relates to transit costs:

$$Log(Crimes)_{ot} = \gamma_t + \gamma_o + \beta_3 Minutes\ to\ Station_{ot} + \epsilon_{3ot} \quad (27)$$

Here, the identification of β_3 comes only from changes over time in the travel time to the closest station, as and when new lines are built, once again conditional on neighborhood and time fixed effects. The first column of Table C.2 shows that, on net, origins that see a reduction in travel time to the closest station see a reduction in criminal activity. As such, if one's residence is now

closer to a new station, they are less likely to engage in crime. The second column of Table C.2 performs a similar exercise, but at the destination level, and speaks a similar narrative: even destinations of criminal activity fall when travel time to the closest stations reduces as a consequence of new lines being built.

Table C.2: The Effects of Travel Time to Station

Travel Time To Station	In Origin Any Crime	In Destination Any Crime	In Origin Any Crime	In Destination Any Crime
Minutes to Station	0.00183** (0.000915)	0.00519* (0.00268)	0.00192* (0.00108)	0.00537** (0.00274)
Observations	3,766	3,766	1,013,054	1,013,054
Data Structure	Orig-Time	Dest-Time	Origin-Dest-Time	
Destination Fixed Effects	No	Yes	Yes	Yes
Origin Fixed Effects	Yes	No	Yes	Yes
Origin-Destination Distance	No	No	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
SE Cluster	Origin	Dest	2-way: Orig Dest	

Notes: Tables show the effect of changes in travel time to the closest station (in minutes) as a result of newly built stations. The first and third column show changes in the origins of crime perpetrators, whereas the second and last columns show the (destination) location of the crime committed. In the final two columns, the data are structured at the origin-by-destination-by-time level.

Finally, in the last two columns, we again leverage the larger dimensionality of the data, with a specification at the $o - d - t$ level:

$$\text{Log}(\text{Crimes})_{odt} = \gamma_t + \gamma_o + \gamma_d + \Xi_{od} + \beta_3 \text{Minutes to Station}_{ot} + \epsilon_{3'odt} \quad (28)$$

Connecting either origins or destinations to stations, on net, across different lines, lower the likelihood of being engaged in criminal activity.

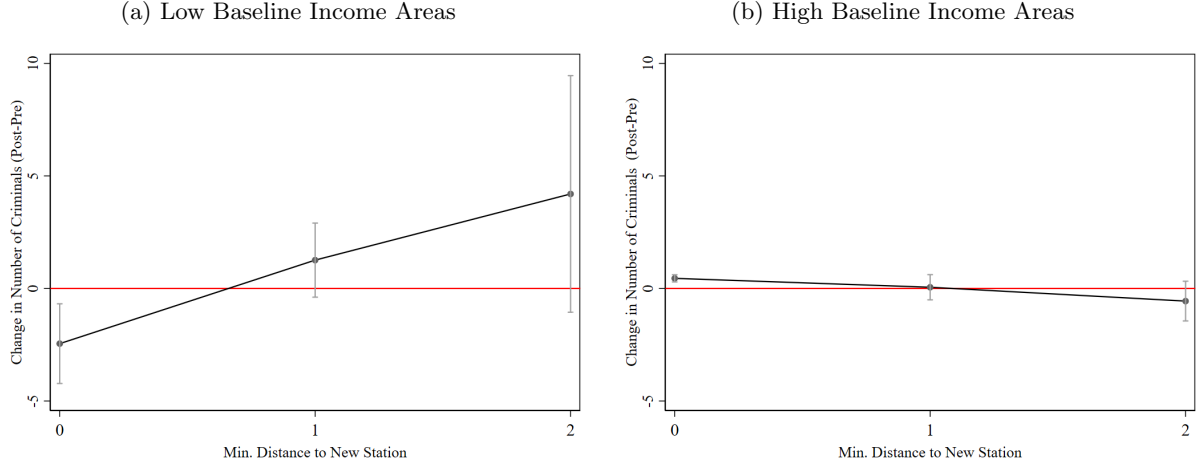
C.2 Distance-based and Event-study Analyses

In documenting the dynamics of the responses, by different types of crime and different types of baseline features of the neighborhoods, we conduct an event study style analysis, pooling the different cable lines, and comparing crime outcomes both before and after the cable was opened, relative to the year it was opened. The years before allow us to test for pre-trends in our outcomes, whereas the years after document the dynamics of the changing relationship. A lack of pre-trends provides confidence in our empirical strategy.

We rely on Figure 4 and define ‘treated’ neighborhoods as those between 0 and 1km from the new station, and ‘control’ neighborhoods as those between 1 and 2km from the new station. We expect these stations to be similar in other respects and so drop all neighborhoods that are further away for this exercise. The treated year is the base period.

In Figure 5, we examine the effects on non-drug crimes, by splitting the sample by baseline criminal activity. In low baseline crime neighborhoods, there are no detectable effects, but in

Figure C.1: Changes in Crime at the Origin by Baseline Income, and Distance (in km) Bins



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-cable 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 income, whereas the right panel is for above median baseline income.

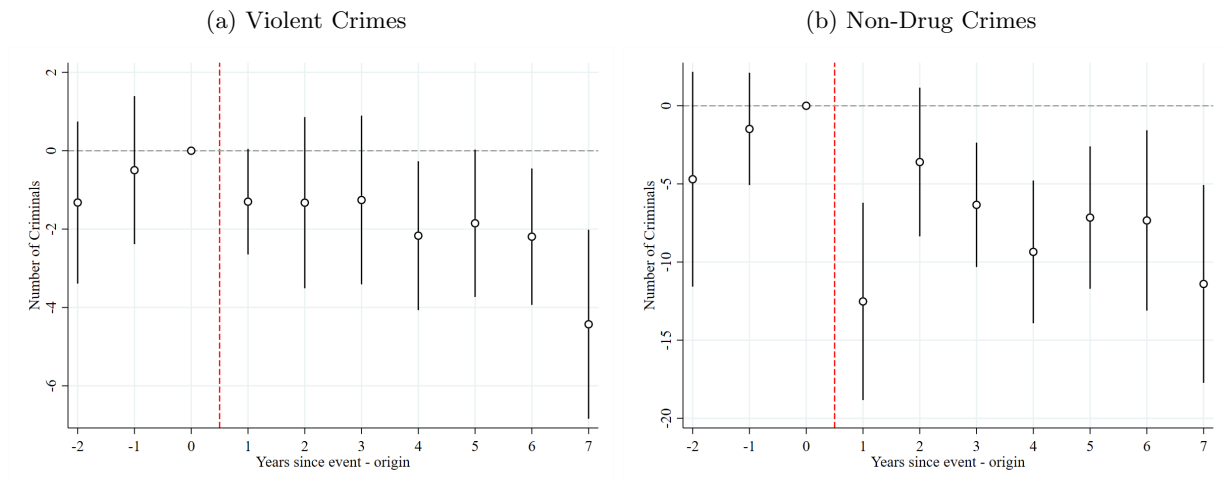
areas that had high criminal activity at baseline, there are sharp drops in non-drug crime-related activity, once again documenting the importance of the heterogeneity across neighborhoods in their baseline economic structure.

In Figure C.1, we conduct a similar exercise, now exploring an additional dimension of heterogeneity – that of different types of crime. We change the type of crime to violent crime, and find a similar pattern that we found in Figure 5 on non-drug crimes: that the effects are concentrated in neighborhoods that had high baseline criminal activity.

Finally, in Figure C.2, we restrict our sample to only low-income neighborhoods, and compare the differences in magnitudes between violent and non-drug crimes. The effects on non-drug crimes are a lot larger than the effects on just violent crime.

Together, these results show a lack of pre-trends leading up to the changes in the establishment of new cable lines, and interesting dynamics following the establishment of cables. Finally, they also confirm the meaningful heterogeneity by baseline access to criminal and economic opportunity.

Figure C.2: Changes in Crime at the Origin by Type of Crime



Notes: Figures show event study plots of the change in crime over time as a function of being 0 to 1km from a new station. Control neighborhoods are 1-2km from the station. Sample is restricted to low-income neighborhoods.

D Model Equilibrium and Comparative Statics

In this section, we show that the equilibrium of our model can be characterized by $3N$ equations (or three equations per neighborhood). We also show in which special cases there exists a unique solution. Finally, by taking $N = 2$ neighborhoods, we simulate the equilibrium for a family of parameters.

D.1 General Equilibrium

Given the model parameters $\{\kappa, \theta_\ell, \theta_c, \eta, \beta, \alpha, \mu, \delta, \lambda, \iota, \rho, \omega\}$, the exogenous location characteristics $\{\mathbf{b}_\ell, \mathbf{a}_\ell, \boldsymbol{\varphi}, \mathbf{K}, \boldsymbol{\xi}, \boldsymbol{\tau}, \mathbf{p}_d\}$ and the reservation utility in the wider economy \bar{U} , the general equilibrium of the model is given by the set of vectors:

$\{\mathbf{w}_\ell, \mathbf{w}_c, \boldsymbol{\theta}, \mathbf{q}, \mathbf{Q}, \boldsymbol{\pi}, \mathbf{A}_\ell, \mathbf{B}_\ell\}$. In the following proposition, we show that $3N$ equations characterize the values of $\{\mathbf{Q}, \mathbf{w}_c, \mathbf{A}_\ell\}$. The other vectors $\{\mathbf{w}_\ell, \boldsymbol{\theta}, \mathbf{q}, \boldsymbol{\pi}, \mathbf{B}_\ell\}$ can be written in terms of $\{\mathbf{Q}, \mathbf{w}_c, \mathbf{A}_\ell\}$, the model parameters and the exogenous location characteristics.

Proposition 1. For $o \in \{1, \dots, N\}$, suppose that $q_o = \xi_o Q_o$. Then, $\{Q_o, w_{oc}, A_{o\ell}\}_{o \in \mathcal{N}}$ are implicitly determined by the following system of equations

$$\begin{aligned} L_o &= \left(\frac{(1-\alpha)A_{o\ell}}{\xi_o Q_o} \right)^{1/\alpha} H_{Eo\ell} + \frac{(1-\alpha)}{Q_o} E[w|o] H_{Ro}, \\ w_{oc} &= (1-p_o) A_{oc} H_{Eoc}^\rho H_{Eo\ell}^\iota, \\ A_{o\ell} &= a_{o\ell} \left(\frac{H_{Eoc}}{L_o} \right)^\lambda. \end{aligned} \tag{29}$$

The variables $H_{Mo\ell}$, H_{Eoc} , H_{Ro} , $E[w|o]$, and $B_{o\ell}$ can be expressed as functions of $\{Q_o, w_{oc}, A_{o\ell}\}_{o \in \mathcal{N}}$.

Proposition 1 says that the general equilibrium can be characterized by the following three sets of equations: (i) the residential and commercial land market clearing conditions; (ii) the endogenous return to crime; (iii) the endogenous productivities in the legitimate sector.

Proof of Proposition 1. First notice that the variables $H_{Eo\ell}$, H_{Eoc} , H_{Ro} , $E[w|o]$, and $B_{o\ell}$ are given by $H_{Ro} = \bar{H} \sum_d \sum_s \pi_{ods}$, $H_{Ed\ell} = \bar{H} \sum_o \pi_{od\ell}$, $H_{Edc} = \bar{H} \sum_o \pi_{odc}$, $E[w|o] = \sum_{ds} \pi_{ds|o} w_{ds}$, and $B_{o\ell} = B_{oc} b_{o\ell} \left(\frac{H_{Eoc}}{L_o} \right)^\omega$. From (5), it follows that

$$\begin{aligned} H_{Ro} &= B_o Q_o^{-(1-\alpha)\eta} W_o^\eta, \\ H_{Ed\ell} &= \sum_o \frac{H_{Ro} B_{o\ell} W_{o\ell|o}^{\kappa-\theta_\ell} w_{d\ell}^{\theta_\ell} \tau_{od}^{-\theta_\ell}}{W B_o}, \\ H_{Edc} &= \sum_o \frac{H_{Ro} B_{oc} W_{oc|o}^{\kappa-\theta_c} w_{dc}^{\theta_c} \tau_{od}^{-\theta_c}}{W B_o}, \\ E[w|o] &= \frac{1}{W B_o} \sum_s B_{os} W_{os|o}^{\kappa-\theta_s} \sum_d \left(w_{ds}^{\theta_s+1} \tau_{od}^{-\theta_s} \right), \\ B_{o\ell} &= B_{oc} b_{o\ell} \left(\frac{A_{o\ell}}{a_{o\ell}} \right)^{\omega/\lambda}. \end{aligned} \tag{30}$$

Here, $W_o^\eta = \left(\sum_s W_{os|o}^\kappa \right)^{\frac{\eta}{\kappa}}$, $W_{os|o}^\kappa = \left(\sum_d w_{ds}^{\theta_s} \tau_{od}^{-\theta_s} \right)^{\frac{\kappa}{\theta_s}}$, $WB_o = \sum_{s'} B_{os'} W_{os'|o}^\kappa$,

$$w_{d\ell} = \alpha \left[(1 - \alpha)^{(1-\alpha)} \frac{A_{d\ell}}{(\xi_d Q_d)^{(1-\alpha)}} \right]^{1/\alpha}, \quad (31)$$

and $\bar{H} \left(\frac{\gamma}{U} \right)^\eta = 1$. As a result, the system of equations given by (29) is a nonlinear system of equations of the variables $\{Q_o, w_{oc}, A_{o\ell}\}_{o \in \mathcal{N}}$. \square

Corollary 1. Suppose that $\omega \rightarrow 0$ and $\lambda \rightarrow 0$, then there is a unique equilibrium $\{\mathbf{w}_\ell, \mathbf{w}_c, \boldsymbol{\theta}, \mathbf{q}, \mathbf{Q}, \boldsymbol{\pi}\}$, where the crime productivities and residential amenities from the legitimate sector are exogenously given by $\mathbf{A}_\ell = \mathbf{a}_\ell$ and $\mathbf{B}_\ell = \mathbf{b}_\ell$, respectively.

The proof of the above corollary follows from Lemma S.1, Lemma S.2 and Proposition S.1 in the supplementary material from Ahlfeldt et al. (2015). Note that as $\omega \rightarrow 0$ and $\lambda \rightarrow 0$, the endogenous crime productivities (\mathbf{A}_ℓ) and endogenous residential amenities from the legitimate sector (\mathbf{B}_ℓ) become exogenous variables. Thus, from (29), we are left with a model in which solving for \mathbf{Q} is enough to characterize the equilibrium. This is what Proposition 1 from Ahlfeldt et al. (2015) shows, that there is a unique \mathbf{Q} , from which the other variables of the model can be determined.

D.2 Commuter and Firm Market Access

Using the objects defined in general equilibrium, one can solve the following system of equations to compute MA measures for both firms and commuters specific to each sector and location:

$$\text{CMA}_{os,t} = \sum_d \frac{\tau_{od,t}^{-\theta_s}}{\text{FMA}_{ds,t}} H_{Eds,t} \quad (32)$$

$$\text{FMA}_{ds,t} = \sum_o \frac{\tau_{od,t}^{-\theta_s}}{\text{CMA}_{os,t}} H_{Ros,t}, \quad (33)$$

where H_{Eds} represents the total number of workers in location d sector s , H_{Ros} represents the total number of individuals that reside in o and work in sector s . Tsivanidis (2023) shows that one can solve for this with data on commuting costs, the number of residents and workers in each sector, and location. This system of equations is just-identified in terms of $\text{CMA}_{os,t}$ and $\text{FMA}_{ds,t}$ as we have one unique equation for each unknown.

D.3 Comparative Statics with Two Neighborhoods

To understand when reductions in transportation cost τ_{od} will import opportunities and when it would export crime, we examine the roles played by our main parameters of interest: the sector choice parameter κ , the spillover externality λ , and transportation elasticities θ_s . We examine whether residents of a location H_{Roc} engage in less crime (import opportunity), or commit more crimes in other neighborhoods H_{Eoc} (export crime) in a simple two-neighborhood case in which neighborhood one has more criminal residents at baseline, and neighborhood 2 is a productive legitimate downtown with a lot of legitimate employment. We study how sectoral choice and location decisions change as we connect these two neighborhoods through improvements in the transportation network.

Specifically, we take $N = 2$, and for these two neighborhoods, we solve the system given by (29). Then, we find the general equilibrium for certain fixed parameters, and present a simulation for the equilibrium values of $\{H_{Eoc}, H_{Roc}\}_{o \in \mathcal{N}}$ as functions of the transportation cost τ_{12} .

We set the parameters of the model to be $\alpha = 0.5$, $\eta = 1.124$, $\rho = -0.5$, $\iota = 0.5$, $\tau_{11} = \tau_{21} = \tau_{22} = 1$, $p_1 = p_2 = 0.5$, and $\xi_1 = \xi_2 = 1$. The exogenous location characteristics are $B_{1c} = 4$, $B_{2c} = b_{1\ell} = b_{2\ell} = 1$, $B_1 = B_2 = 1$, $A_{1c} = A_{2c} = a_{1\ell} = 1$, $a_{2\ell} = 4$, and $L_1 = L_2 = 0.1$. As previously mentioned, the choices of these values are motivated by a baseline scenario in which neighborhood 1 has a lot of crime residents given its large criminal amenity fundamental B_{1c} , while neighborhood 2 is a productive downtown with large fundamental productivity $a_{2\ell} = 4$.

Figures D.1-D.4 show the graphs of $\{H_{Eoc}, H_{Roc}\}_{o \in \mathcal{N}}$ as functions of the transportation cost τ_{12} , and for different values of $\{\kappa, \lambda, \theta_c, \theta_\ell\}$. Recall that H_{Roc} represents the equilibrium residential population living in neighborhood o working in the crime sector, and H_{Edc} represents the equilibrium labor supplied to destination d in the crime sector.

Figure D.1: H_{Roc} and H_{Edc} as functions of τ_{12} , changing κ .

(a) H_{Roc} for neighborhoods 1 and 2, and two different values of κ . For this graph $\{\lambda, \theta_c, \theta_\ell\} = \{-0.2, 3, 7.01\}$. (b) H_{Edc} for neighborhoods 1 and 2, and two different values of κ . For this graph $\{\lambda, \theta_c, \theta_\ell\} = \{-0.2, 3, 7.01\}$.

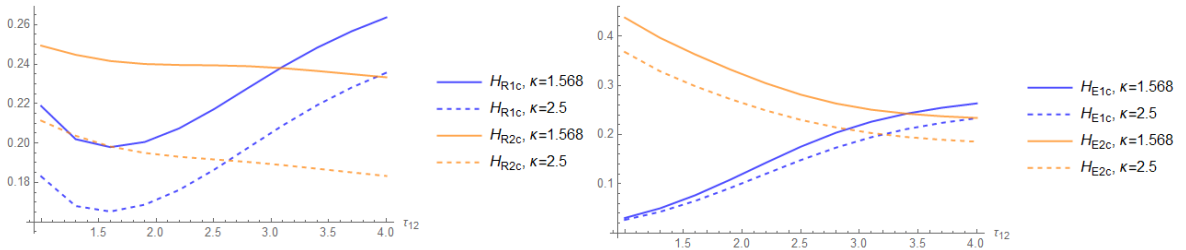


Figure D.2: H_{Roc} and H_{Edc} as functions of τ_{12} , changing λ .

(a) H_{Roc} for neighborhoods 1 and 2, and two different values of λ . For this graph $\{\kappa, \theta_c, \theta_\ell\} = \{1.568, 3, 7.01\}$. (b) H_{Edc} for neighborhoods 1 and 2, and two different values of λ . For this graph $\{\kappa, \theta_c, \theta_\ell\} = \{1.568, 3, 7.01\}$.

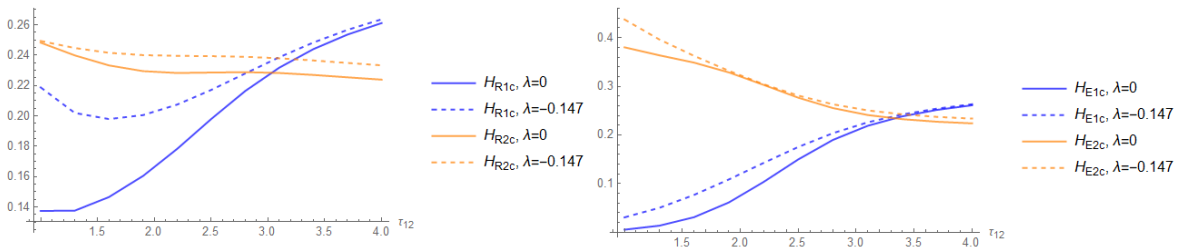
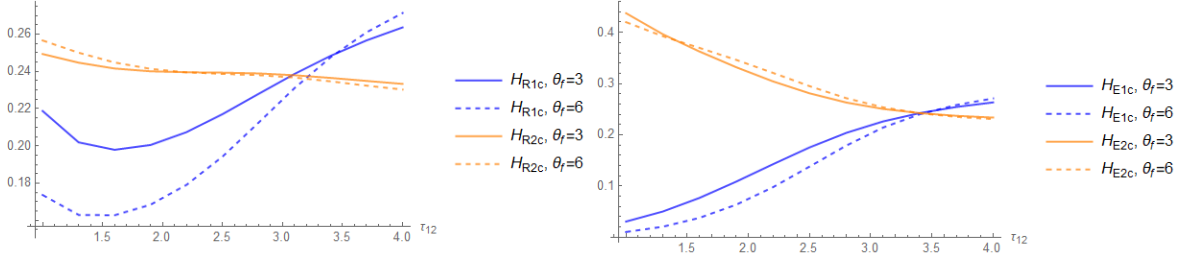


Figure D.1a shows the graph of H_{Roc} for different values of κ . Recall that κ captures the relative labor supply elasticity across sectors: a large κ means that individuals tend to easily switch sectors as relative returns change. As expected, when τ is large and, hence, neighborhoods are disconnected, there are more criminals living in neighborhood 1. As we connect this neighborhood to downtown by reducing τ_{12} , individuals tend to switch to the legitimate sector as opportunity is imported. Importantly, this comparative static depends on

κ : the larger is κ , the more individuals will switch towards legitimate employment as the relative returns of legitimate work increases when they are connected to productive downtown.

Figure D.3: H_{Roc} and H_{Edc} as functions of τ_{12} , changing θ_ℓ .

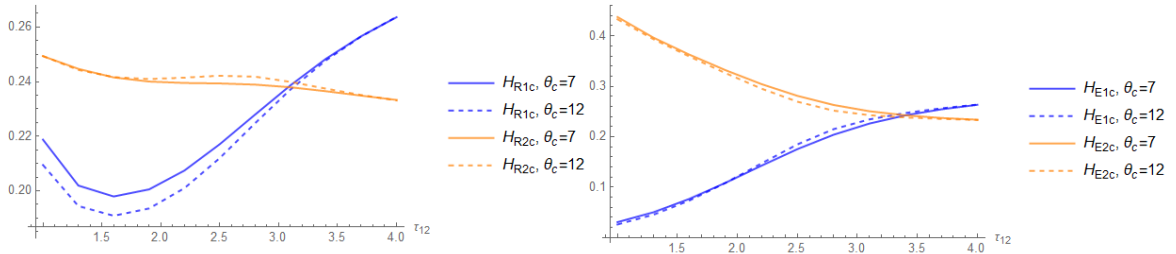
(a) H_{Roc} for neighborhoods 1 and 2, and two different values of θ_ℓ . For this graph $\{\lambda, \theta_c, \kappa\} = \{-0.2, 3, 1.568\}$. (b) H_{Edc} for neighborhoods 1 and 2, and two different values of θ_ℓ . For this graph $\{\lambda, \theta_c, \kappa\} = \{-0.2, 3, 1.568\}$.



A decrease in λ (from $\lambda = 0$ to $\lambda = -0.147$), meaning larger negative externalities from crime on legitimate productivity, shifts H_{Roc} upward for both neighborhoods (see Figure D.2a). This is due to the fact that, with a large negative externality of crime on legitimate workers, the relative returns of legitimate work relative to crime work will not increase as much given that with some exporting of crime overall productivity in downtown, and hence wages, will be lower given that some criminals will find it profitable to commit crime there.

Figure D.4: H_{Roc} and H_{Edc} as functions of τ_{12} , changing θ_c .

(a) H_{Roc} for neighborhoods 1 and 2, and two different values of θ_c . For this graph $\{\lambda, \kappa, \theta_\ell\} = \{-0.2, 1.568, 7.01\}$. (b) H_{Edc} for neighborhoods 1 and 2, and two different values of θ_c . For this graph $\{\lambda, \kappa, \theta_\ell\} = \{-0.2, 1.568, 7.01\}$.



Finally, we explore the effect of an increase in the value of θ_ℓ (from $\theta_\ell = 3$ to $\theta_\ell = 6$) over H_{Roc} . This parameter captures the sensitivity of legitimate workers to commute times. A large θ_ℓ implies that changes in commute costs will have a large impact on legitimate workers' location decisions. Note that this larger sensitivity to commute costs generates a larger sectoral shift from crime towards legitimate work in neighborhood one (see D.3a). A similar behavior can be observed as θ_c changes (see Figure D.4a).

On the other hand, Figure D.1b shows the graph of H_{Edc} , which measures the number of criminal workers in a neighborhood, for different values of κ . An increase in κ shifts H_{Edc} downward for both neighborhoods, again, because it allows for larger sectoral changes and hence more importing of opportunity and more legitimate workers in the city overall. A decrease in λ (from $\lambda = 0$ to $\lambda = -0.147$) shifts H_{Edc} upward for both neighborhoods (see Figure D.2b) since larger negative externalities of crime imply that legitimate returns will be lower in the city

overall and hence there will be smaller sectoral shifts toward that sector.

D.4 Welfare Decomposition Derivation

In this section, we derive the formula used for the welfare decomposition. This is derived starting from market clearing conditions. By the properties of the Frechet draws, the total amount of efficiency units net of commute costs provided by location n to location i sector s is given by:

$$w_{ds}\tau_{od}^{-1}H_{Eds} = \pi_{ods}\bar{y}_o$$

where \bar{y}_o is the total income of workers in location o and is given by:

$$\bar{y}_o \equiv \left(\sum_s B_{os} W_{os}^\kappa \right)^{\frac{1}{\kappa}}$$

and:

$$W_{os} \equiv \left(\sum_d w_{ds}^{\theta_s} \tau_{od}^{-\theta_s} \right)^{\frac{1}{\theta_s}}$$

In terms of payments to legitimate workers and commercial floorspace, denoting $y_{d\ell}$ as total legitimate output in produced in location d , from perfect competition we know that:

$$y_{d\ell} = w_{d\ell}H_{Ed\ell} + q_d L_{d\ell}$$

Commercial floorspace market clearing implies that:

$$\varrho_o Q_o L_o = L_{o\ell} Q_o$$

and residential market clearing is:

$$(1 - \varrho_o) Q_o L_o = (1 - \beta) \pi_o \bar{y}_o$$

The endogenous returns of criminals are determined by:

$$w_{dc} = (1 - p_d) A_{dc} H_{Edc}^\rho H_{Edl}^\iota$$

Denoting X_o as total expenditure on consumption goods by residents in location o , from the Cobb Douglas assumption we know that total expenditure will be equal to a β share of total income of residents in that neighborhood.

$$X_o = \beta \pi_o \bar{y}_o$$

Finally, from goods market clearing we must have that:

$$\sum_d y_{d\ell} = \sum_o X_o$$

We assume that the social planner uses a utilitarian welfare function with weights for the change in real income from each location given by total worker income of residents of that

location. That is, the change in aggregate welfare is given by:

$$d \log \bar{U} = \sum_o \pi_o \bar{y}_o [d \log(\bar{y}_o) - \beta d \log(P_o) - (1 - \beta) d \log(Q_o)] ,$$

where P_o is the consumption price index in location o , which, due to our assumption of a freely tradable good which is also the numeraire, will be equal to $P = 1$ for every neighborhood within the city. The change in residents income is given by:

$$d \log(\bar{y}_o) = \sum_s \sum_d \pi_{os|o} \pi_{ods|os} d \log w_{ds} - \sum_s \sum_d \pi_{os|o} \pi_{ods|os} d \log \tau_{od} + \frac{1}{\kappa} \sum_s \pi_{os|o} d \log(B_{os}) \quad (34)$$

Combining the commuter market clearing condition as well as the endogenous returns to criminal activity, one can relate the weighted-average change in total resident income to the change in criminal returns and payments to legitimate workers' legitimate output:

$$\begin{aligned} \sum_o \bar{y}_o \pi_o d \log(\bar{y}_o) &= \rho \sum_d w_{dc} H_{Edc} d \log H_{Edc} + \iota \sum_d w_{dc} \frac{H_{Edc}}{H_{Ed\ell}} H_{Ed\ell} d \log(H_{Ed\ell}) + \dots \\ &\dots + \sum_d y_{d\ell} d \log(y_{d\ell}) - \sum_d L_{d\ell} q_d d \log(q_d) + \sum_d y_{d\ell} d \log(A_{d\ell}) + \dots \\ &\dots - \sum_o \sum_s \sum_i \bar{y}_o \pi_o \pi_{os|o} \pi_{ods|os} d \log \tau_{od} + \frac{1}{\kappa} \sum_o \sum_s \bar{y}_o \pi_o \pi_{os|o} d \log(B_{os}) \end{aligned}$$

Combining the goods market clearing condition with the demand for consumption by every location o , one can relate the weighted-average change in destination legitimate output to the change in the price index:

$$\sum_d y_{d\ell} d \log(y_{d\ell}) = \beta \sum_o \pi_o \bar{y}_o d \log(P_o)$$

Similarly, by combining residential and commercial floorspace market clearing, one can relate total expenditure in floorspace to the change in the amount of income that goes to absentee landlords as:

$$\sum_o L_{o\ell} q_o d \log(q_o) + \sum_o (1 - \varrho_0) Q_o L_o d \log(Q_o) = \sum_o Q_o L_o d \log(Q_o)$$

Finally, using our specifications for amenity and productivity externalities, and assuming that, since we can only identify the change in relative amenities $B_{o\ell}/B_{oc}$, we can normalize $B_{oc} = 1$ as in the inversion, then:

$$\sum_d y_{d\ell} d \log(A_{d\ell}) = \lambda \sum_d y_{d\ell} d \log(H_{Edc})$$

And since we have specified amenity externalities as being a function of the ratio and essentially we are assuming that $d \log(B_{oc}) = 0$, then:

$$d \log(B_{o\ell}) = \omega d \log(H_{Edc})$$

Substituting these equations to the social planner's problem, we get:

$$\begin{aligned}
d \log \bar{U} = & - \sum_o \sum_s \sum_i \bar{y}_o \pi_o \pi_{os|o} \pi_{ods|os} d \log \tau_{od} \\
& + \frac{\omega}{\kappa} \sum_o \sum_s \bar{y}_o \pi_o \pi_{os|o} d \log (H_{Eoc}) + \lambda \sum_d y_{d\ell} d \log (H_{Edc}) \\
& + \rho \sum_d w_{dc} H_{Edc} d \log H_{Edc} + \iota \sum_d w_{dc} H_{Edc} d \log (H_{Ed\ell}) \\
& - \sum_o Q_o L_o d \log (Q_o)
\end{aligned}$$

which is the expression shown in the main body of the text.