# Spatial Mobility, Economic Opportunity, and Crime

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#### \*Preliminary\*

#### 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 the decision of individuals to choose where to work and whether to engage in criminal activity, with important 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 needed to identify key parameters of the model. We leverage the roll out of a cable car system to causally isolate how changes in transportation costs affect the location and sector choices of workers and criminals. Our counterfactual exercises indicate that overall criminal activity in the city is reduced and total welfare is improved when increasing connectedness for almost all neighborhoods.

**Keywords:** Crime, transit networks, segregation, Medellín **JEL Codes:** K42, J46, J24

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# 1 Introduction

Income, economic opportunity and criminal activity are all unequally spatially distributed in cities across the developed and developing world (Cutler and Glaeser, 1997; Athey et al., 2020). 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 such segregation, neighborhoods are often strong predictors of both economic opportunity and criminal activity (Kling et al., 2007; Chyn, 2018; Chetty and Hendren, 2018a; Jacob, 2004; Melnikov et al., 2019).

Canonical models of crime (Becker, 1968; Ehrlich, 1973) which depict criminal activity as a rational choice in the face of limited legitimate economic alternatives would then suggest that investing in transportation infrastructure to better connect poor populations segregated from opportunity to more economically active parts of the city could reduce criminal activity. 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.<sup>1</sup> We investigate these claims by asking: does improving connectedness between segregated and economically unequal parts of a city predominantly import opportunity or export crime?

Empirically evaluating the results of transportation infrastructure investments on both localized and aggregate income, employment, and crime is, however, difficult as these are jointly determined results of a spatial equilibrium. That is, 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 plant closings) 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 addresses these issues (Ahlfeldt et al., 2015; Donaldson and Hornbeck, 2016; Tsivanidis, 2018; Zárate, 2019).

A second set of challenges arise in finding variation for identification and obtaining the necessary granular data. We leverage the roll out of a public transit system over a decade to identify parameters of the model; however, to do so we need exceedingly rare

<sup>&</sup>lt;sup>1</sup>See, for instance, the example of Atlanta "The Myth That Mass Transit Attracts Crime Is Alive in Atlanta" in Bloomberg (Dec, 2014), and the case of Baltimore "Addicts, crooks, thieves': the campaign to kill Baltimore's light rail" covered by the Guardian (Aug, 2018). Indeed, there is no shortage of events to study 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 whether to invest in the expansion of transportation infrastructure linking prosperous, affluent areas to struggling neighborhoods.

data on the flows of crime from origin to destination. That is, over the period, we need to know where a criminal lives and where they travel to commit crimes in addition to analogous data on flows of legitimate workers. Having such data allows for transparent identification and a tractable analysis that does not rely on the structure of the model.

We use the census 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 surveys. These novel individual-level administrative data allow us 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, house prices, and the location of firms 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 period of study by which previously disconnected poor neighborhoods with varying degrees of baseline criminality became linked to both high crime areas and high income, low crime areas.

We start by documenting reduced form evidence that these expansions decreased the likelihood that inhabitants of poor, high crime neighborhoods near the newly built stations were arrested for crimes, and that lower commute times predict higher formal employment. That is, poor 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, and some low baseline 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 sector and space under the changing 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, 2018) and structurally estimate the effects of several cable transportation system expansions on the equilibrium level and spatial distribution of employment, income, 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.<sup>2</sup> We build on previous work by incorporating the role of crime, modelling the sectoral choice (the choice between crime and legitimate employment) of individuals. Our innovation includes inter-sectoral spillovers whereby crime may have negative externalities on other forms of economic activity, even as new legitimate economic activity changes the returns to crime (Rossi-Hansberg et al., 2010; Bryan et al., 2019). 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.

The strength of this generalizable framework is that it allows us to conduct various counterfactual exercises with alternative degrees and directions of expansion of the transportation infrastructure. These counterfactual 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?

We simulate new cable lines that were officially proposed, but for which construction was recently halted. We find that newly connected areas see a sharp reduction in individuals engaging in criminal activity. When low-income, low opportunity areas are connected to work opportunities in other parts of the city, individuals are more likely to switch to legitimate activities. As such, neighborhood segregation is a meaningful driver of aggregate crime in the city. The counterfactual (proposed) lines we construct increase net GDP by between 2.4 and 2.9 billion USD.

We also 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 low-crime parts of the city, greater connectedness for all but the most connected neighborhoods at baseline yields aggregate reductions in crime, increases in output and welfare, and reductions in inequality. Indeed, the largest gains accrue when connecting neighborhoods with the lowest formal-sector market access at baseline.

Our work speaks to three distinct literatures. First, we build on recent evidence of the distinction between residential segregation and "experienced segregation" or "consumption segregation" in the urban economics literature (Athey et al., 2020; Kling et al., 2007; Chetty and Hendren, 2018a,b) by documenting that reducing "employment segregation"

 $<sup>^{2}</sup>$ The Stable Unit Treatment Value Assumption is violated as all neighborhoods are indirectly affected when new transit lines are built.

by linking poor, marginalized neighborhoods to employment opportunities in distant parts of the city can have profound impacts on criminal activity (Melnikov et al., 2019). Our paper is the first to our knowledge to study criminal participation in a spatial equilibrium framework as relative returns to formal work and crime change across neighborhoods.

Second, we contribute to the recent series of papers developing spatial equilibrium models by adapting these models and methods to the study of criminal activity (Ahlfeldt et al., 2015; Donaldson and Hornbeck, 2016). A few recent studies have used these techniques to study similar expansions in urban transportation infrastructure (Tsivanidis, 2018; Zárate, 2019). We allow for multiple sectors of employment and estimate crime externalities on neighborhood amenities and firm productivity.

Finally, this approach also represents a contribution to the the crime economics literature on the link between employment and criminality (Becker, 1968). Recent crime studies have validated the link between legitimate employment opportunities and criminality using variation from trade shocks (Dell et al., 2019; Dix-Carneiro et al., 2018), job loss (Bennett and Ouazad, 2018; Khanna et al., 2020) and public policies (Khanna et al., 2019; Fu and Wolpin, 2017) to establish causality. We build on this evidence by showing how crime and prosperity is linked across neighborhoods that differ in access to economic opportunity. Notably, we examine how mass transit systems change this access to opportunities, resulting in a different configuration of both the spatial distribution and overall levels of crime across the city.

# 2 Data

We combine administrative data on households, jobs, crime, commuting times, and house prices from various sources. We link individual records using government-issued individual identification numbers and dates of birth. Since we leverage identification from changes to neighborhood access, we treat the neighborhood as the primary geographic unit in the analysis. There are 269 neighborhoods with an average size of 373 thousand square meters, and 7,756 inhabitants.<sup>3</sup>

The first source of data are from three waves of the *Sistema de Selección de Beneficiarios para Programas Sociales* (SISBEN II and SISBEN III, System for the Identification of Potential Beneficiaries of Social Programs) from the Department of National Planning (2009). SISBEN I from 2002, SISBEN II from 2005, and SISBEN III from 2010 allow us

<sup>&</sup>lt;sup>3</sup>While possible to conduct the analysis at a more disaggregated block level, one may be concerned of making the data too granular (Dingel and Tintelnot, 2020). Since we have a large number of inhabitants per neighborhoods, we use the neighborhood as our unit of observation, and show reduced form relationships at both the neighborhood and block level.

to track individuals, their households and residential locations over time. The SISBEN waves are Censuses of approximately the 65-80% of the poorest 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, 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 all individuals arrested in Medellin between 2002 and 2015, whether or not they were convicted. These data contain type of crime committed, the date and neighbourhood of arrest, and identifier 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).<sup>4</sup>

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.

To know the location of the workplaces, we obtain data from the *Camara de Com*ercio 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.

We augment these data with the Land Registry Data from the Medellin's Cadastre, 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 mobility 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 on the road

 $<sup>{}^{4}</sup>$ If an individual was first arrested for violent crime and later for property crime, they show up as an arrest for violent crime.

Figure 1: Segregation in Crime and Formal Work by Neighborhood, 2010 (a) Share of Neighborhood Engaged in Crime (b) Share of Formal Jobs by Neighborhood



Note: Spatial distribution of where individuals arrested in 2010 reside (left panel), and where individuals in 2010 work (right panel). The dotted lines show the the metro lines in 2010. The data are aggregated to 249 neighborhoods.

network in Medellin to construct historical commute times for public transport and cars. We do so using the Network Analysis toolkit from ArcGIS, which also allows us to build counterfactual commute times that we use in the model.<sup>5</sup>

# 3 Neighborhoods, Jobs and Crime in Medellín

## 3.1 Segregation and Urban Transit in Medellín

Located in the north-western region of Colombia, Medellín is the second largest city after the capital, Bogota. 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 249 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.

<sup>&</sup>lt;sup>5</sup>We describe the construction of the transport network in Section B in the Appendix.

Figure 2: Roll out of Transit Lines and Change in Commute Times, 2002-2015(a) Transit Lines and Commute Times, 2002 (b) Transit Lines and Commute Times, 2015



Note: Average commute times originating from neighborhoods in 2002 (left panel) and 2015 (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 249 neighborhoods.

Most criminal activity is concentrated in areas that were historically associated with drug cartels. These include the north-eastern sections of the city, the western edge of the city, and the eastern extremity. There are also pockets of of crime near downtown: the center of the city, 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 crime is more prevalent around the edges of the city, economic activity is more starkly present in the center, at the downtown (Figure 1). The commuting infrastructure, as a result, was built to more easily bring people downtown and improve the access to formal jobs. There are also pockets of activity in each of the different quadrants of the city, most notably in the south-west.

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. In order 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.

Figure 2 shows how over the period, as new transit lines were added to the city, 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 in the north-eastern 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 the 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 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 3 from CCSPJP (2009)), placing our analysis among a handful that study motivations behind participating in crime in high-crime environments. The high homicide rates are a result of fights among urban militias, local gangs, drug cartels, criminal bands, and paramilitaries based in surrounding areas.<sup>6</sup> 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 (2002-2018) rates have fallen substantially since to about 21 per 100,000 inhabitants (Figure 3). Between 2005-13, 12% of all males (across all age groups) were at some point arrested, while the arrest rate for females was only 1%. Younger individuals are more likely to be engaged in drug trafficking and consumption, whereas slightly older individuals are involved in violent crimes (homicides, extortions, and kidnapping), and the oldest still are involved in property crime.

In ongoing research, Blattman et al. (2018) document Medellín's criminal world as hundreds of well-defined street gangs (*combos*) which control local territories and are organized into hierarchical relationships of supply, and protection by the *razones* at the

<sup>&</sup>lt;sup>6</sup>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).



Figure 3: 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 Public y la Justicia Penal*. The right panel shows the average homicide rates in 2010 in cities across the world, where Medellín is represented in red.

top of the hierarchy. They confirm that gangs are mainly profit-seeking organizations, earning money from protection, coercive services such as debt collection and drug sales. 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.<sup>7</sup> Knowing this, paramilitaries and gangs actively recruit idle youth that are *amurrao* (local slang, literally: 'sitting on the wall') and without a formal sector job.

An interview with El Mono (p191) documents the recruitment process: "those guys would hang out around here and be nice to me and say 'come over here, have a bit of money'." Having a formal sector job means that one is not "hanging around the neighborhood" when the gangs come recruiting. A desirable outside option would be a job with benefits and social security, yet those with formal sector jobs pay extortion fees to gangs.<sup>8</sup> Indeed, the options are often presented as an occupational choice: "are you gonna work [for the gang] or do a normal job?"<sup>9</sup>

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) estimate that foot soldiers of the combos receive well above national minimum wage whereas *combo* leaders

<sup>&</sup>lt;sup>7</sup>See interview with Gato, p264 and interview with Armando, p197.

<sup>&</sup>lt;sup>8</sup>See interview with El Peludo, p184.

<sup>&</sup>lt;sup>9</sup>See interview with Notes, p193

earnings "put them in the top 10% of income earners in the city."<sup>10</sup>

These numbers are high relative to most contexts, but are representative of cities in Latin America. The US has an incarceration rate more than six times the typical OECD nation, where one in ten youths 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, in some regards, arrests in our context are similar to high-crime regions in many parts of the developing world, and especially Latin America (Dell et al., 2018).

# 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 4 that plots the commute times in our individual-level data for different types of criminal activity and for formal work. It shows that formal workers travel farthest to access their jobs. 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. This is true of not only low level crimes like petty theft, but also drug trafficking and violent crime.

The differences in commute times have meaningful implications for what would happen when new transit lines are built. On the one hand, the raw densities may suggest that criminal activity is more sensitive to commute times than formal work. If so, changes to commute times may have a sharper effect on the spatial distribution of criminal activity than that on formal employment. On the other hand, the densities may indicate the formal work is strongly segregated and confined to certain pockets of the city. As such, reaching those pockets require a fair amount of commute time. New transit lines that reduce these commute times increase access to these pockets of formal opportunities, and may induce individuals on the margin away from criminal activity. This latter implication of segregation is consistent with the maps shown in Figure 1.

<sup>&</sup>lt;sup>10</sup>During the demobilization of militias in the mid-2000s, many were encouraged to join the formal sector, given identity cards and medical cards (Rozema, 2018). Yet, this disparity in costs across social benefit regimes, discourages formal sector re-integration.



Figure 4: 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 different types of crime). We use the road maps, transit networks, and travel times by different modes of transport to estimate commute times for each origin-destination pair in our data. We restrict our data to one individual per observation, where we choose the first arrest in 2010 for the type of crime.

#### 4.2 Difference-in-Differences: Effects of Cables Lines on Crime

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

Consider crimes committed in neighborhood d (we use d for destination of where the criminal activity occurred). A simple difference-in-differences (DiD) design would suggest the following specification:

$$Log(Crimes)_{dt} = \gamma_t + \gamma_d + \beta_1 \left( Log[Dist \ to \ New \ Stations]_d \times Post_t \right) + \epsilon_{1dt}$$
(1)

Here,  $\gamma_t$  are time fixed effects that control for changes in aggregate crime and transportation across neighborhoods, and  $\gamma_d$  are neighborhood fixed effects that account for time-invariant neighborhood level differences. Let  $Log(Distance \ to \ New \ Stations)_d$  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,  $\beta_1$  is the DiD estimator for the effect of being further away from a newly built cable station on crime. Yet, this  $\beta_1$  only tells us the effects of new lines on crime destinations. Cable lines also connect neighborhoods where potential criminals or workers may come from. An analogous question arises, as to what happens at the origin o when new cables are constructed? Are individuals more likely to take advantage of the cable to go and engage in criminal activity elsewhere in the city, or more likely to use it to access jobs in other areas? A similar specification describes what happens at the origin:

$$Log(Crimes)_{ot} = \gamma_t + \gamma_o + \beta_{1'} (Log[Dist \ to \ New \ Stations]_o \times Post_t) + \epsilon_{1'ot}$$
(2)

Effects on	Destinations	Effects on Origins		
Any Crime	Violent Crime	Any Crime	Violent Crime	
$0.0970^{**}$ (0.0438)	$0.180^{***}$ (0.0523)	$0.0693^{***} \\ (0.0232)$	$\begin{array}{c} 0.154^{***} \\ (0.0316) \end{array}$	
$3,\!486$	3,416	$3,\!192$	$2,\!996$	
Destination-by-Time		Origin-by-Time		
Yes	Yes	No	No	
No	No	Yes	Yes	
No	No	No	No	
Yes	Yes	Yes	Yes	
Dest	Dest	Origin	Origin	
	Effects on Any Crime 0.0970** (0.0438) 3,486 Destinati Yes No No Yes Dest	Effects on Destinations Any CrimeDestinations Violent Crime0.0970**0.180*** (0.0438)(0.0523)3,4863,416Destination-by-Time YesYesYesYesNoNoNoNoNoNoYesYesDestDest	Effects on Destinations Any CrimeEffects Any Crime $0.0970^{**}$ $0.180^{***}$ $0.0693^{***}$ $(0.0438)$ $(0.0523)$ $(0.0232)$ $3,486$ $3,416$ $3,192$ Destination-by-Time YesOriginYesYesNoNoNoYesNoNoYesDestDestOrigin	

Table 1: The Effects of New Cable Lines on Crime

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

Table 1 describes these regressions for one of the new cable lines: Linea K. In the first two columns we examine the changes to criminal activity at destinations, and in the last columns, 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 Table 1 suggest that when a neighborhood is connected to a Linea K station criminal activity at that neighborhood actually falls. Being further 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 last two columns of Table 1 present an interesting complementary result: when

residences are connected to the cable, fewer criminals are associated as coming from those residences. As such, while the first two columns are indicative of what happens to criminal destinations when connected to transit, the last two determine what happens to criminals originating from such locations. Both suggest that locations closer to new stations see a fall in crime.

Yet, such an analysis ignores the richer dimensionality of the data. Indeed, if origins and destinations are close-by then it may be no surprise that origins and destinations display similar patterns. As such, by reformulating the data to be at the originby-destination-by-time level, we can control for time invariant features of the origindestination pair, such as the distance between them  $\Xi_{od}$ , along with time invariant features of destinations  $\gamma_d$  and origins  $\gamma_o$ .

$$Log(Crimes)_{odt} = \gamma_t + \gamma_o + \gamma_d + \Xi_{od} + \beta_2 \left( Log[Dist \ to \ New \ Stations]_{o/d} \times Post_t \right) + \epsilon_{2odt}$$
(3)

Here,  $\beta_2$  is again the DiD coefficient, and we can examine it as a consequences 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.

	Destination Stations		Origin Stations	
	Any Crime	Violent Crime	Any Crime	Violent Crime
Log(Distance to Station)xPost	$0.115^{**}$	0.218***	$0.0724^{**}$	$0.163^{***}$
	(0.0470)	(0.0573)	(0.0302)	(0.0374)
Observations	$794,\!808$	$727,\!608$	$794,\!808$	$727,\!608$
Data Structure	Origin-by-Destination-by-Time			
Destination Fixed Effects	Yes	Yes	Yes	Yes
Origin Fixed Effects	Yes	Yes	Yes	Yes
Origin-Destination Distance	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
SE Cluster	Two Way: Destination and Origin			

Table 2: The Effects of New Cable Lines on Crime

Notes: The first two columns show difference-in-differences estimates for being close to a station, and crime destinations. The last two columns show the effects on origins (residences) of crime perpetrators. The data are at the origin-by-destination-by-year level.

Table 2 reinforces the results in Table 1 by once again showing that the closer one is to the new station, the greater is the decrease in criminal activity once the new line is introduced. This is true for the destinations of criminal activity (first two columns of



Figure 5: 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.

Table 2), and the originating residences of these criminals (last two columns of Table 2).

## 4.3 Heterogeneity by Neighborhood Economic Structure

While this reduced form analysis is informative of what happens on net at places near new transit centers, the net outcomes clearly depending on complex underlying relationships. Tables 1 and 2 suggest that when new stations are built, crime outcomes decrease in connected neighborhoods, and less criminals originate from such neighborhoods. This may perhaps be that being connected, now allows youth to have access to legitimate employment opportunities in other parts of the city, lowering the attractiveness of being involved in crime.

This may be likely, if for instance, criminal activity is more localized than formal sector employment. If most crime centers around local street gangs, then not being able to easily to go 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 can easily access legitimate activity in other parts of the city. Yet, such a narrative would imply that if the economic structure of the neighborhood were different, then being connected may have had an opposite effect. Suppose, for instance, a neighborhood with no street gangs were 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 formal sector jobs. But we may also have youth from these newly connected neighborhoods joining criminal enterprises in other neighborhoods that they now have easy access to. Theoretically, this suggests that what we saw in Tables 1 and 2 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 and distance traveled to formal jobs after new cable lines were built.

To document the changes, we must aim to compare regions near the newly built stations to those further away. Yet, we should not think of regions further away as 'control neighborhoods,' as all neighborhoods will be indirectly affected. To be transparent, we show the effects along on various distance bins to as to non-parametrically describe these relationships.

In Figure 5 we see that there were sharp reductions in criminal activity originating from neighborhoods near the stations (between 0 and 1km). Yet, this reduction is confined to neighborhoods that have high baseline levels of crime, and to neighborhoods that have low income. As such, in low-crime and in high-income neighborhoods, the change in criminal activity as a function of the distance to the new station, is relatively flat. The heterogeneity in criminal responses is indicative of how the distribution of local opportunities is important in determining the change in crime as a result of changes in access to different neighborhoods. Together, these results show meaningful heterogeneity in the response to criminal activity by baseline access to criminal and economic opportunity. This is a nuance we can unpack with our structural framework.

### 4.4 Event Study Analyses

Finally, in documenting the dynamics of the responses, by different types of crime and different types of baseline features of the neighborhoods, we can conduct an event study style analysis, where 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



Figure 6: Changes in Non-Drug Crime 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.

the dynamics of the changing relationship. A lack of pre-trends provides confidence to our empirical strategy.

We rely on Figure 5 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 6, 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 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 7, 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 be violent crime, and find a similar pattern that we found in Figure 6 on non-drug crimes: that the effects are concentrated in neighborhoods that had high baseline criminal activity.

Finally in Figure 8, we restrict our sample to only low income neighborhoods, and compare the differences in magnitudes between the violent and the non-drug crimes. The effects on non-drug crimes are a lot larger than the effects on just violent crime.



Figure 7: Changes in Violent Crime at the Origin by Baseline Crime

Notes: Figures show event study plots of the change in violent 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.

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.

#### 4.5 Travel Time and Net Effects Across Lines

Given the different possible countervailing effects, what should determine the net effects is how long it takes to reach the closest of the stations so as to access the broader transit network. This time to a cable station *Minutes to Station<sub>ot</sub>* 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:

$$Log(Crimes)_{ot} = \gamma_t + \gamma_o + \beta_3 Minutes \ to \ Station_{ot} + \epsilon_{3ot} \tag{4}$$

Here, the identification of  $\beta_3$  comes only from changes over time in the travel-time to the closest station, as and when new lines are built, once again conditional of neighborhood and time fixed effects. The first column of Table 3 shows that, on net, origins that see a reduction in travel time to the closest station see a reduction in criminal activity. As such,

Figure 8: 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.

if ones residence is now closer to a new station, they are less likely to engage in crime. The second column of Table 3 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 reduce as a consequence of new lines being built.

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

$$Log(Crimes)_{odt} = \gamma_t + \gamma_o + \gamma_d + \Xi_{od} + \beta_{3'} Minutes \ to \ Station_{ot} + \epsilon_{3'odt} \tag{5}$$

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

#### 4.6 Panel Gravity Equations and Neighborhood-by-Time Shocks

Our description so far tells us the effects of being near a newly built rail line. Yet, it does not speak to the consequences on changes in the travel time between neighborhoods. Indeed, that is what we show 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.

Consider what we show in Table 3. Being near a station reduces crime. Yet, as this is a difference-in-differences analysis, all it tells us is that it reduces crime *relative* 

Travel Time To Station	In Origin In Destination Any Crime		In Origin In Destination Any Crime	
Minutes to Station	$\begin{array}{c} 0.00183^{**} \\ (0.000915) \end{array}$	$0.00519^{*}$ (0.00268)	$0.00192^{*}$ (0.00108)	$\begin{array}{c} 0.00537^{**} \\ (0.00274) \end{array}$
Observations	$3,\!192$	3,486	794,808	794,808
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

#### Table 3: The Effects of Travel Time to Station

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 origins of crime perpetrators, whereas the second and last column 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.

to other neighborhoods. As neighborhoods are connected, these results may indeed be driven by increases in criminal activity to neighborhoods further away from stations. For instance, if living near a station means a criminal can travel further away to newer neighborhoods, then crime may increase in such neighborhoods further away, even as it reduces in neighborhoods near the newly connected station.

The inherent nature of such general equilibrium consequences necessitates a spatial general equilibrium model to make meaningful statements about what happens to crime and legitimate activity. Yet, to identify important parameters of the model, we need to leverage the roll out of the cable in a manner that is no longer confounded by other differences across neighborhoods and time.

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  $\theta_c$  is higher than for legitimate employment, then crime is more sensitive to travel time, and there may be a greater dispersion in criminal activity as a result of changes to travel time.

In order to execute this analysis, we use the information on travel times between any origin and destination neighborhood pair, and how that changes as and when new cable lines are introduced. This variable  $Travel Time Minutes_{odt}$  varies at the origin-bydestination-by-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 simultaneously 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 at the neighborhoods over time, in a way that somehow happens to be correlated with distance to the station would be a worrying confounder.

Fortunately, the richness of our data allow us to control for all such effects, by including origin-by-time fixed effects  $\gamma_{ot}$  and destination by time fixed effects  $\gamma_{dt}$ :

$$Log(Crimes)_{odt} = \gamma_{ot} + \gamma_{dt} + \Xi_{od} + \beta_4 Travel Time Minutes_{odt} + \epsilon_{4odt}$$
(6)

We return to Equation 6 later in our analysis as it helps causally identify the crucial parameters of our model. Here,  $\gamma_{ot}$  and  $\gamma_{dt}$  account for neighborhood-by-time level shocks, such as new gang wars, or changes policing that change over time by neighborhood.  $\Xi_{od}$ controls for time-invariant differences across neighborhood-pairs. As such, the remaining threat to identification would be if there were time varying shocks to origin-destination pairs that were unaccounted for by the neighborhood-by-time fixed effects.

We show later that  $\beta_4$  is meaningfully informative of crucial economic elasticities that drive the spatial distribution of crime and legitimate activity across the city.

In Table 4, we estimate Equation 6. Reductions in the travel time between origins o and destinations d will raise the amount of criminal activity that flows from origin o to destination d. The corresponding elasticities with respect to travel time are -0.079 for all crimes, and a similar -0.076 for violent crimes.

Yet, as we show below in the model, what is equally relevant is the change in flows of legitimate employment as a result of these new cables. If legitimate employment is less responsive to travel costs, then new lines are less likely to greatly affect the flow of formal sector jobs.

In the last column of Table 4, we replace the outcome to be formal-sector work, and find that the travel-time elasticity of formal sector flows is lower than that of crime, at about -0.014. We return to Table 4 again below and discuss how  $\beta_4$  causally inform our model's parameters.

Travel Time From			
Origin To Destination	Any Crime	Violent Crime	Formal Work
Minutes From Origin to Destination	-0.0791***	-0.0755***	-0.0158***
	(0.00364)	(0.00406)	(0.00613)
Observations	$658,\!695$	336,189	466,708
Data Structure	Origin-Dest-Time		
Destination-by-Time FEs	Yes	Yes	Yes
Origin-by-Time FEs	Yes	Yes	Yes
Distance Between Origin and Destination	Yes	Yes	Yes
SE Cluster	Two Way: Destination and Origin		

#### Table 4: The Effects of Travel Time From Origins to Destinations

Notes: Tables show the effect of changes in travel time between origin-destination pairs on the resulting flows in crime and formal 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.

# 5 Model

Our economic geography framework is based on recent developments in models of spatial mobility (Ahlfeldt et al., 2015; Tsivanidis, 2018; Donaldson and Hornbeck, 2016). We adapt these models to incorporate the role played by criminal activity. We model the sectoral choice (the choice between crime and legitimate employment) of individuals as a function of firm market access and commuter market access. Importantly, we include inter-sectoral spillovers whereby crime may have negative externalities on other forms of economic activity, even as new economic activity changes the returns to crime (Rossi-Hansberg et al., 2010; Bryan et al., 2019).

Consider a city embedded within a wider economy. The city consists of a set of discrete neighborhoods indexed by o = 1, ..., N, populated by an endogenous measure of  $\overline{H}$  workers who are perfectly mobile within the city and the larger economy. Workers are risk neutral and have preferences for housing and consumption of a final good. They can participate in two sectors:  $s \in \{c, f\}$  where c stands for crime, and f stands for formal work. A worker  $\omega$  chooses where to live o, where to work d, and which sector to work in s to maximize her utility:

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

The utility function depends on consumption of the final good,  $C_{ods}$ , which we take to be the numeraire, consumption of housing,  $H_{ods}$ , iceberg commute costs incurred when commuting from origin o to destination d,  $\tau_{od} \geq 0$ , as well as an idiosyncratic shock,  $\epsilon_{ods}$ , and  $\beta \in (0, 1)$ .<sup>11</sup> This shock represents idiosyncratic reasons that motivate individuals to choose different o, d, s even when their observable characteristics are the same.

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

$$H(\vec{\epsilon}) = \exp\left[-\sum_{o} B_o\left(\sum_{s} B_{os}\left(\sum_{d} \epsilon_{ods}^{-\theta_s}\right)^{\frac{\kappa}{\theta_s}}\right)^{\frac{\eta}{\kappa}}\right], \text{ with } \eta < \kappa < \theta_s \quad \forall s.$$

Given the observed shocks, individuals decide where to reside, which sector to work in, and where to work. The parameters  $\eta$ ,  $\kappa$ ,  $\theta_s$  control productivity dispersion across locations, sectors, and workplaces respectively. On the other hand, 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.

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

$$\pi_{ods} = \underbrace{\left(\frac{B_o Q_o^{-(1-\beta)\eta} W_o^{\eta}}{\sum_{o'} B_{o'} Q_{o'}^{-(1-\beta)\eta} W_{o'}^{\eta}}\right)}_{\pi_o} \underbrace{\left(\frac{B_{os} W_{os|o}^{\kappa}}{\sum_{s'} B_{os'} W_{os'|o}^{\kappa}}\right)}_{\pi_{os|o}} \underbrace{\left(\frac{w_{ds}^{\theta_s} \tau_{od}^{-\theta_s}}{\sum_{d'} w_{d's}^{\theta_s} \tau_{od'}^{-\theta_s}}\right)}_{\pi_{ods|os}}, \tag{7}$$

where  $W_o^{\kappa} = \sum_{s'} W_{os'|o}^{\kappa}$  is an origin-specific wage index, and  $W_{os|o}^{\theta_s} = \sum_{d'} w_{d's}^{\theta_s} \tau_{od'}^{-\theta_s}$  is an origin-sector specific wage index.<sup>12</sup>

The choice probabilities imply that, conditional on having chosen an origin and a sector, individuals are more likely to work in a destination that has a large commutediscounted return  $w_{ds}^{\theta_s} \tau_{od}^{\theta_s}$  relative to the other destinations. On the other hand, conditional on their origin o, 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. Finally, individuals are more likely to choose an origin neighborhood o if it has large amenities  $B_o$ , low residential floorspace

<sup>&</sup>lt;sup>11</sup>Iceberg commute costs affect utility directly, but this specification is isomorphic to one in which commute costs reduce effective wages earned by individuals due to the time used for commuting.

<sup>&</sup>lt;sup>12</sup>The nested frechet assumption allows us to decompose the overall probability of choosing an originsector-destination into three different components.  $\pi_{ods|os}$  the probability of choosing a destination conditional on having chosen an origin and a sector,  $\pi_{os|o}$  the probability of choosing a sector conditional on your origin, and the probability of choosing an origin o. Note that  $\sum_{d} \pi_{ods|os} = \sum_{s} \pi_{os|o} = \sum_{o} \pi_{o} = 1$ .

prices  $Q_o$ , and that is close to destinations that are generally profitable  $W_o$ , relative to all other origins.

Workers are assumed to be mobile between the city and the larger economy, which delivers a constant utility  $\overline{U}$ . Thus, spatial equilibrium requires expected utility equalization:

$$\bar{U} = \mathbb{E}\left[\max_{ods}\{V_{ods}\}\right] = \Gamma\left(\frac{\eta-1}{\eta}\right) \left(\sum_{o} B_o \left[Q_o^{-(1-\alpha)}W_o\right]^\eta\right)^{1/\eta},\qquad(8)$$

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 ocurs under conditions of perfect competition and constant returns to scale. We assume that the production technology takes the Cobb-Douglas form. Output of the final good in block d,  $y_d$  is:

$$y_d = A_{df} \left( H_{Edf} \right)^{\alpha} \left( L_{df} \right)^{1-\alpha} ,$$

where  $A_{df}$  is final goods productivity,  $H_{Edf}$  is workplace formal employment,  $L_{df}$  is commercial floorspace in destination d, and  $\alpha \in (0, 1)$ .

Firms choose their block of of production and their inputs of workers and commercial floorspace to maximize profits, taking as given final goods productivity  $A_{df}$ , the distribution of idiosyncratic utility, goods and factor prices  $w_{df}$ ,  $q_d$ , and the location decisions of other firms and workers. The FOC of firm in block d delivers:

$$q_d = (1 - \alpha) \left(\frac{\alpha}{w_{df}}\right)^{\alpha/(1-\alpha)} A_{df}^{1/(1-\alpha)}$$
(9)

#### 5.1.1 Land Market

We assume that there is a competitive floorspace market at each destination. Specifically, a competitive floor-space provider allocates its total floorspace,  $L_d$ , by choosing a fraction  $\theta_d \in [0, 1]$  for commercial floorspace and  $(1 - \theta_d)$  for residential floorspace to maxmize total profits. This firm takes as given commercial and residential prices  $q_d, Q_d$ , 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:

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

This yields the following no arbitrage condition:

$$\begin{aligned}
\theta_d &= 1 & \text{if} \quad q_d > \xi_d Q_d \\
\theta_d &\in [0, 1] & \text{if} \quad q_d = \xi_d Q_d \\
\theta_d &= 0 & \text{if} \quad q_d < \xi_d Q_d
\end{aligned} \tag{10}$$

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:<sup>13</sup>

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

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  $(1 - \theta_d) L_d$ . Using utility maximization for each worker and taking expectations over the distribution for idiosyncratic utility, residential floor market clearing is:

$$\mathbb{E}[\ell_{ods}|o]H_{Ro} = (1-\theta_o)L_o , \qquad (11)$$

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

Commercial land market clearing requires that demand for commercial floor space equals the supply of floor space allocated to commercial use in each location  $\theta_d L_d$ . The commercial land market clearing condition is:

$$\left(\frac{(1-\alpha)A_{df}}{q_d}\right)^{1/\alpha} H_{Edf} = \theta_d L_d \tag{12}$$

<sup>&</sup>lt;sup>13</sup>We 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.

### 5.2 Crime Sector and its Effect on Productivity & Amenities

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

$$w_{dc} = (1 - p_d) A_{dc} H^{\rho}_{Edc} H^{\iota}_{Edf} \tag{13}$$

where  $\rho \in [-1, 0]$  and  $\iota \in [0, 1]$ , where  $H_{Edc}$  and  $H_{Edf}$  are total number of criminals and total number of formal workers in d. This specification captures congestion forces of multiple criminals commiting crimes in the same destination through  $\rho$  and the potential extra attractiveness of a location d depending on the number of formal workers that are present. 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  $p_d$  using the average homicide capture rates at each destination across our sample.<sup>14</sup>

Motivated by the urban literature on crime (Bryan et al., 2019), we assume that the criminal sector has a negative effect on the productivity of firms at a destination. Specifically, overall productivity,  $A_{df}$ , at destination d is given by:

$$A_{df} = a_{df} \Upsilon^{\lambda}_{dc}$$

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

$$\Upsilon_{dc} \equiv \frac{H_{Edc}}{K_d} , \qquad (14)$$

where  $H_{Edc}$  is the total number of criminals in destination d and  $K_d$  is total land area in destination d.<sup>15</sup>

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

<sup>&</sup>lt;sup>14</sup>As shown in Figure A.1 the average arrest rate is low. In this sense, using this empirical estimate of the probability of capture allows us to convert observed captured criminals into total number of criminals working in each destination.

<sup>&</sup>lt;sup>15</sup>We originally modeled these externalities with an iceberg spillover term to capture the fact that crime in one neighborhood could affect productivity in an adjacent neighborhood:

where  $\nu$  is a parameter that captures how relevant crime at different distances is for productivity, and  $\tau_{dk}$  are the iceberg commuting costs between blocks d and k. We estimated strong rates of decay, and so simplified the model.

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

$$\frac{B_{of}}{B_{oc}} = b_{of} \Upsilon^{\omega}_{oc}.$$
(15)

## 5.3 Equilibrium

Given model parameters { $\kappa, \theta_f, \theta_c, \eta, \beta, \alpha, \mu, \delta, \lambda, \iota, \rho, \omega$ }, the reservation utility in the wider economy  $\bar{U}$ , vectors of exogenous location characteristics { $\mathbf{B}_o, \mathbf{B}_c, \mathbf{b}_f, \varphi, K, \xi, \tau, A_c, p_d$ } the general equilibrium of the model is given by the vectors { $w_f, w_c, \theta, q, Q, A_f, B_f, \pi$ }, and total city population  $\bar{H}$  such that the population mobility condition holds (8), origin and sector probabilities are given by choice probabilities in (7), there is formal labor market clearing, there is commercial (12) and residential land market clearing (11), criminal wages are endogenously determined by equation (13), firms make zero profits (11), and there is no arbitrage between alternative uses of land (10).

In Appendix C.1 we have a broader discussion of the model's equilibrium. In Appendix C.2, we study a special case of two neighborhoods, and examine further when reductions in transportation costs  $\tau_{od}$  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  $\tau_{od}$ , in comparative static exercises: the sector choice parameter  $\kappa$ , the spillover externality  $\lambda$ , and transportation elasticities  $\theta_s$ .

# 6 Parameter Estimation

### 6.1 Sector-Specific Commuting Elasticities

Following the literature, we parameterize iceberg commuting as an exponential function of commuting time:

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

where time<sub>od</sub> is the average travel time in minutes across public and private transportation modes of moving from o to d.

To estimate commuting elasticities, we use the fact that we observe criminal flows across neighborhoods. From the model, one can derive the following gravity equation relating commuting flows across municipalities and iceberg costs:

$$\log\left(\pi_{ods|os,t}\right) = \underbrace{\beta_s}_{\delta \cdot \theta_s} \cdot \text{time }_{od,t} + \gamma_{ot} + \gamma_{dt} + \epsilon_{odst}$$

 $\pi_{ods|os,t}$  is the share of workers that commute to location d form o working in sector s in year t.  $time_{od,t}$  is the average commuting time across municipalities od, t in year t,  $\gamma_{ot}$  are origin-time fixed effects,  $\gamma_{dt}$  are destination-time fixed effects,  $\epsilon_{odst}$  captures measurement error observed in the data.

Our goal is to recover the parameters  $\theta_s$  after knowing  $\beta_s$  and  $\delta_d$ . We estimate this equation via PPML to include zero commuting flows between municipalities and find  $\hat{\theta}_c = 7.01$  and  $\hat{\theta}_f = 1.584$ .

### 6.2 Sectoral Labor Supply Elasticity

We now discuss how we recover  $\kappa$ , which corresponds to the labor supply elasticity across sectors that governs the reallocation of workers from the criminal sector to the formal economy. We define the **sector-specific commuter market access (CMA)** for location n, sector s as:

$$CMA_{os} \equiv \sum_{d} w_{ds}^{\theta_s} \tau_{od}^{-\theta_s} , \qquad (16)$$

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:

$$\mathrm{FMA}_{ds} \equiv \sum_{o} \frac{\tau_{od}^{-\theta_s}}{\mathrm{CMA}_{os}} H_{Ros} \; ,$$

as firm market access. One can solve the following system of equations to compute MA measures for both firms and commuters specific to each sector and location:

$$CMA_{os} = \sum_{d} \frac{\tau_{od}^{-\theta_s}}{FMA_{ds}} H_{Eds}$$
(17)

$$FMA_{ds} = \sum_{o} \frac{\tau_{od}^{-\theta_s}}{CMA_{os}} H_{Ros} , \qquad (18)$$

where  $H_{Eds}$  represents the total amount 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 (2018) shows that one can solve for this with data on commuting costs, number of residents and workers in each sector and location.

To arrive at estimation equations containing  $\kappa$ , recall that the sector s-choice probability in time period t conditional on being in origin o is:

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

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

This yields a regression equation specific to sector s that would allow us to identify  $\kappa$ :

$$\ln(\pi_{ost|o}) = \kappa \frac{1}{\theta_s} \ln(CMA_{os,t}) + \gamma_o + \gamma_t + \eta_{ost}$$
(19)

We focus on s = f, as the first stage using a shift-share instrument to capture variation due to exogenous changes in the returns to formal work was stronger.<sup>16</sup> We estimate  $\hat{\kappa} = 1.568$ , as in the first column of Table 5.

**Identification** Given that equation 19 expresses a labor supply relationship, there is an endogeneity concern when estimating  $\kappa$ .  $\ln(\pi_{oft|o})$  and  $\frac{1}{\theta_f} \ln \text{CMA}_{of,t}$  will be correlated due to shifts of the relative labor supply curve in addition to shifts along the relative labor supply curve.  $\kappa$ , 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  $\kappa$ will be biased.

To address this, we estimate the specification in equation 19 using shift-share instruments capturing firm productivity shocks that are correlated with but exogenous to wages and formal employment in Medellín. These external productivity instruments serve as relative labor demand shifters; formal sector firms experiencing exogenous productivity shocks will adjust wages and employment in Medellín accordingly. Shifts in only formal labor demand capture relative employment and wages along the same relative labor sup-

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

 $<sup>^{16}</sup>$ We were unable to pass weak first-stage tests using the Don Berna variation in returns to crime. As robustness, since taking a log of a small number magnifies error, we also estimate:

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

ply curve. Thus, our LATE will reflect only variation from shifts along relative supply, allowing us to identify  $\kappa$ .

Note, that these Bartik instruments will correspond to *destinations* in our data, whereas equation 19 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 17 to calculate origin-level instruments, where  $z_{dt}$  is the destination level shock to formal sector productivity and  $\tilde{z}_{ot}$  captures shocks aggregated to the origin level.

$$\tilde{z}_{ot} = \sum_{d} z_{dt}^{\theta_f} \tau_{odt}^{-\theta_F}$$

	(1)	(2)	(3)	(4)
	$\kappa$	$\lambda$	$\omega$	$ ho$ & $\iota$
	Log(Formal)	Log(Productivity)	Log(Amenity)	Log(Crime/Total) +
				$ heta_C \delta  au_{od}$
$\text{Log CMA}_{fot}$	$1.568^{*}$ (0.878)			
$\operatorname{Log} \operatorname{Crime}_o$		-0.147	-0.450**	-0.197**
		(0.108)	(0.181)	(0.0829)
$\operatorname{Log} \operatorname{Formal}_{o}$				0.0437
				(0.0349)
Observation Level	Origin-Year	Destination	Origin	Origin-Destination-Year
Method	2SLS	GMM	GMM	2SLS
Instrument(s)	Shift-Share	Don Berna	Don Berna	Shift-Share, Don Berna
F-Stat (of IV)	52.58	-	-	22.97
Fixed Effects	Year, Origin	-	-	Origin
Observations	1,856	260	205	33,531
SE Cluster	Origin	Conley HAC	Conley HAC	Destination

Table 5: Estimating  $\kappa, \lambda, \omega, \rho, \iota$ 

Notes: Table shows the estimation of additional parameters. Log  $\text{CMA}_{fot}$  is the natural log of formal sector commuter market access values by neighborhood. Log  $\text{Crime}_o$  is the number of crimes in a neighborhood. Log Formal<sub>o</sub> is the number of formal sector workers in a neighborhood. The outcome in the last column is the crime-share adjusted for commute costs (Log(Crime/Total) +  $\theta_C \delta \tau_{od}$ ). \* Indicates significance at 10% level, \*\* indicates significance at 5% level.

### 6.3 Residential Choice Elasticity

We now discuss how to estimate the residential choice elasticity. Recall that the probability of someone choosing to live in origin o in period t is defined as:

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

where  $B_{ot}$  is an unobserved residential amenity,  $Q_{ot}$  is the residential floor-space price, and  $W_{ot} = (CMA_{oc,t}^{\kappa} + CMA_{of,t}^{\kappa})^{\frac{1}{\kappa}}$ . Taking the log of both sides we derive:

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

Written in terms of observables, the corresponding estimation equation becomes:

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

where we set  $1 - \beta = 0.25$  following Ahlfeldt et al. (2015),  $\gamma_t$  is a time-fixed effect, and  $\epsilon_\eta$  is the error term. We need an instrument for  $(\ln W_{ot} - (1 - \beta) \ln Q_{ot})$  to identify  $\eta$  since the residential amenity is unobserved. We use the Bartik shock aggregated to the origin level described in the previous section on estimating the sector-choice Fréchet parameter, since it correlates with CMA<sub>of,t</sub> and not the residential amenity. Our estimate is  $\hat{\eta} = 1.124$ .

## 6.4 Criminal Productivity Externality

To estimate the crime externality parameter  $\lambda$ , we follow Ahlfeldt et al. (2015) to derive moment conditions using the structural productivity residual. Using first order conditions of the production function for the formal sector with respect to labor and floor space, we derive the following structural relationship linking wages  $w_d$ , the productivity residual  $a_{dt}$ , land/factor prices  $q_{dt}$ , and the crime externality  $\Upsilon_{dc,t} = \frac{H_{Edc,t}}{K_d}$ :

$$w_d = \alpha (1-\alpha)^{\frac{1-\alpha}{\alpha}} a_d^{\frac{1}{\alpha}} q_d^{\frac{\alpha-1}{\alpha}} \Upsilon^{\frac{\lambda}{\alpha}}$$

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

$$\Delta log\left(\frac{a_{dt}}{\overline{a}_t}\right) = (\alpha - 1)\Delta log\left(\frac{q_{dt}}{\overline{q}_t}\right) - \alpha\Delta log\left(\frac{w_{dt}}{\overline{w}_t}\right) - \lambda\Delta log\left(\frac{\Upsilon_{dc,t}}{\overline{\Upsilon}_t}\right) , \qquad (20)$$

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

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

where h(Z) is the vector of instruments discussed below. We implement estimation of the crime externality parameters using GMM and find  $\hat{\lambda} = -0.147$  (Table 5, column 2).

Identification Like Ahlfeldt et al. (2015), we want to identify  $\lambda$  using only variation coming from changes in commuting access and the resulting change in the crime externality rather than other reasons for changes in  $\Delta log(\frac{a_{dt}}{\overline{a}_t})$  (e.g., changes in the distribution of productivity in Medellín due to a change in zoning laws). Thus, we want an instrument capturing only the former source of variation. Specifically, we construct instruments based off of how far neighborhoods were from locations affected by the gang areas of a local crime lord (i.e., Don Berna) who was extradited in 2009. The extradition led to a spike in homicides in the neighborhoods that were under Berna's control, and we leverage this to identify the effects of how increases in crime affect economic activity. Variation across different bands of distances help identify  $\lambda$ .

### 6.5 Criminal Residential Amenity

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

$$\pi_{os|o} = \frac{L_{os}}{L_o} = \frac{B_{os} W^{\kappa}_{os|o}}{B_{oc} W^{\kappa}_{oc|o} + B_{of} W^{\kappa}_{of|o}}$$
(22)

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

$$\frac{L_{of}}{L_{oc}} = \frac{B_{of} W_{of|o}^{\kappa}}{B_{oc} W_{oc|o}^{\kappa}} = b_o \Upsilon_o^{\omega} \frac{W_{of|o}^{\kappa}}{W_{oc|o}^{\kappa}}$$
(23)

where:

$$\frac{B_{of}}{B_{oc}} = b_{of} \Upsilon_o^{\omega} \tag{24}$$

Like before, we can take the difference across periods and divide by the geometric means to get:

$$\Delta \ln \left(\frac{b_{ot}}{\overline{b}_{ot}}\right) = \Delta \ln \left(\frac{L_{oft}}{\overline{L}_{oft}}\right) - \Delta \ln \left(\frac{L_{oct}}{\overline{L}_{oct}}\right) - \omega \Delta \ln \left(\frac{\Upsilon_{ot}}{\overline{\Upsilon}_{ot}}\right) - \kappa \Delta \ln \left(\frac{W_{of|ot}}{\overline{W}_{of|ot}}\right) + \kappa \Delta \ln \left(\frac{W_{oc|ot}}{\overline{W}_{oc|ot}}\right)$$
(25)

As in the case of the crime productivity externality, we can get the following structural moment condition for each sector:

$$\mathbb{E}\left[h(Z)\Delta log\left(\frac{b_{ost}}{\bar{b}_{ost}}\right)\right]$$
(26)

and estimate  $\hat{\omega} = -0.45$  in Table 5, column 3.

## 6.6 Returns to Crime

Recall, that the share of criminals living in origin o choosing to commit a crime in destination d is:

$$\pi_{odc|oc} = \frac{w_{dc}^{\theta_c} \tau_{od}^{-\theta_c}}{\sum_{d'} (w_{d'c}/\tau_{od'})^{\theta_c}}$$

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

$$\pi_{odct|oc,t} = \frac{\tilde{A}_{dc,t}^{\theta_c} H_{dc,t}^{\rho\theta_c} (H_{df,t})^{\iota\theta_c} \tau_{od}^{-\theta_c}}{\sum_{d'} (w_{d'c}/\tau_{od'})^{\theta_c}}$$

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

where  $\tilde{A}_{dc,t} = (1 - p_{d,t})A_{dc,t}$ . This can be translated into the following estimation equation:

$$log(\pi_{odct|oc,t}) = \rho \theta_c log(H_{dc,t}) + \iota \theta_c log(H_{df,t}) - \theta_c \tau_{od,t} - \gamma_o + \epsilon_{od,t}$$
(27)

This depends only on observables  $(\pi_{odct|oc,t}, H_{dc,t}, H_{df,t}, w_{df,t}, \tau_{od,t})$  and separately estimated parameter  $\theta_c$ . Under this setup, we control for unobserved criminal productivity  $\tilde{A}_{dc,t}$  using fixed effects. We find  $\hat{\rho} = -0.197$  and  $\hat{\iota} = 0.0427$  (Table 5, column 4).

#### Identification

A number of unobservables could cause the total number of criminals in a given destination  $H_{dc,t}$  to covary with the share of criminals commuting from origin o to destination d. For example, d could be the headquarters for a gang with a strong presence in o in period t. We have assumed that crime affects productivity, so there is a simultaneity problem when estimating  $\iota$ . As such, we use the Don Berna instrument to identify  $\rho$  and the Bartik shocks to identify  $\iota$ .

## 6.7 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  $\delta$  we follow the growing consensus in the literature (Ahlfeldt et al., 2015; Tsivanidis, 2018; Zárate, 2019) and set it to  $\delta = 0.01$ . In terms of the externality parameters, we estimate them using the previously mentioned strategy and obtain  $\nu = 0.0783$ ,  $\lambda = 0.2084$ .

#### 6.8 Model Inversion

Given the value of the parameters, we can recover the fundamentals of the model  $\{B_{os}, A_d\}$ .<sup>17</sup> In order to do so, we first solve for commuter and firm market access given observed residential and labor decisions through equations 17 and 18.

Given the recovered  $\{CMA_o, FMA_o\}$ , one can obtain the model-implied wages from the sectoral labor supply equation:

$$H_{ds} = w_{ds}^{\theta} \mathrm{FMA}_{ds}$$

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

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

<sup>&</sup>lt;sup>17</sup>For this version of the results we assume that  $B_o = 1 \quad \forall o$ , and that  $\xi_d = 1 \forall d$ .

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

$$\frac{\pi_{of|o}}{\pi_{oc|o}} = \frac{B_{of}}{B_{oc}} \left[ \frac{\text{CMA}_{of}^{1/\theta_f}}{\text{CMA}_{oc}^{1/\theta_c}} \right]^k$$

Thus, we can recover the relative amenities  $B_{of}/B_{oc}$  by fitting the number of formal 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? 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 we should target with transportation improvements. Here, we reduce the average commute time at each origin neighborhood, and examine the welfare and criminality consequences of such an intervention.

## 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, or are under construction. First, we 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. We then evaluate the impacts of a new cable line that is currently under construction on the north-western part of the city.

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, and low formal sector market access. The north-western part has relatively less crime and relatively higher market access. The differences in the outcomes describe how baseline characteristics affect the equilibrium outcomes for both criminality and welfare.

#### 7.1.1 The Eastern Tram Line

As shown in Figure 9, in 2016 the government of Medellin invested in a tram line that connected neighborhoods in the eastern part of Medellin to the CBD.





*Notes* : This map shows the average minutes of commute by neighborhood of origin across destinations. The pink line shows the tram that was built in 2016.

Importantly, these were relatively poor neighborhoods where criminals tended to live. Figure 10 shows the percentiles of the Sectoral Firm Market access for both crime and formal work in 2015 across neighborhoods. The map shows a stark contrast between crime and formal work FMA in this part of the city. Specifically, crime FMA is large relative to formal FMA there: individuals living in these neighborhoods tended to choose the criminal sector instead of the formal 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 formal CMA for connected neighborhoods since they will now be able to commute to neighborhoods with large returns for formal 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 first 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 in 2016 and solve



#### Figure 10: Sectoral Firm Market access, 2015

Notes: These maps show the percentiles of recovered Sectoral Firm Market Access for both crime and formal work in 2015.

the model for the endogenous variables.<sup>18</sup> We then analyze the economy's response to the commute cost shock.

The main results of this exercise are shown in Figure 11. The map plots the percent change in the probability of becoming a criminal conditional on living in a particular origin o,  $\pi_{oc|o}$ , given the change in commute costs induced by the tram in 2016.

According to our estimates, the tram increased formal CMA relative to criminal CMA in treated neighborhoods, therefore reducing the probability of becoming a criminal by up to 12%. 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 formal work opportunities. In order to see this more clearly, Figure 12 shows the relationship between the decline in average commute costs and the change in the probability of becoming a criminal by origin. The relationship is non-linear, showing larger effects for neighborhoods with larger declines in average commute costs.

So far, we have discussed the extensive margin of sector choice. We now explore the intensive margin of crime by focusing on the destination decisions conditional on sector and origin. That is, we explore the effect of the reduction in commute times in the probability of committing crime by destinations for one particular origin. In order

 $<sup>^{18}</sup>$ In 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.

Figure 11: Change in Probability of Becoming a Criminal by Origin



*Notes* : The 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.

Figure 12: 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.

to study this we focus on the eastern-most neighborhood of Medellin, which saw the largest decline in average commute times. Figure 13 shows the change in the probability of committing a crime by destination conditional on becoming a criminal and living in this neighborhood.

According to the model, conditional on having chosen to become a criminal, the decline in commute times allows individuals to commit crimes in more profitable destinations. 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 13: Change in Probability of Commiting a Crime by Destination



*Notes* : The map shows the model implied change in the probability of committing a crime by destination conditional on living in the easternmost neighborhood,  $\pi_{odc|oc}$ , across destinations.

Finally, we study the welfare effects of this particular investment in transportation infrastructure. in order to do so, 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. Performing this exercise, we find that building the tram increased expected utility in the city by 2.34%. Focusing on GDP, we find that the tram line increased steady state GDP by 1.6%. Considering the costs of building the line, this represents a NPV increase in GDP of 2.88 billion dollars.<sup>19</sup>

#### 7.1.2 The North-West Cable Line

We now study the sector choice and welfare impacts of a cable line that is currently under construction. The government of Medellín is constructing in a new cable line that connects the north western part of the city to the rest of the transportation network. This line is planned to start operating at the end of 2020. Figure 14 shows the location of this cable line together with the average time commuting by origins.

Based on Figure 10, we know that the north-western part of Medellin is a high crime Firm Market access region, which reveals that criminals tend to live in these neighborhoods. Importantly, Figure 10 shows that these neighborhoods have relatively large Formal Firm Market access as well, meaning that formal workers tend to live in these neighborhoods too. Thus, these neighborhoods have relatively large access to criminal,

 $<sup>^{19}\</sup>mathrm{We}$  use a 10% discount rate across a 50 year time horizon. Cost estimates are obtained from the Government of Medellin.



*Notes* : This map shows the average minutes of commute by neighborhood of origin across destinations. The pink line shows the cable line that is projected to start operations by the end of 2020.

but also to formal employment opportunities.

In order to evaluate the welfare effects of the cable line we construct counterfactual commute times considering the new public transport stations. As in the previous section, 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 15 shows the main results of this exercise. The map plots the percent change in the probability of becoming a criminal for each neighborhood in Medellin. According to the model, the new cable line reduced the probability of becoming a criminal in treated neighbors by as much as 7%. Importantly, comparing to the tram 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.

The smaller effect on the probability of becoming a criminal is due to one main reason: the new cable line is going to connect neighborhoods that were already relatively well connected to the public transport system. The overall change in Formal Firm Commuter Market access for these neighborhoods will not be as large as it was for the much more disconnected neighborhoods in the eastern part of Medellin. The smaller increase in relative Commuter Market access explains the relatively smaller decline in the probability of becoming a criminal in this counterfactual.<sup>20</sup>

Finally, we evaluate the change in expected welfare due to the construction of the new

<sup>&</sup>lt;sup>20</sup>Similar 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.

#### Figure 15: Change in Probability of Becoming a Criminal by Origin



*Notes* : The 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.

cable line assuming that there is no in nor out-migration from Medellin. Consistent with the results found so far, the model predicts a positive welfare impact of only 0.083%, which is sizably smaller to that of the tram line which was 2.34%. The smaller welfare impact is due, on the one hand, mechanically to the smaller size of the infrastructure project and thus to the smaller decline on 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 amount of criminals in the city. Nonetheless, when translating these impacts into GDP, we find that the new cable line increased steady state GDP by 1%. This translates into a NPV increase in GDP of 2.39 billion dollars, making it a highly profitable investment.<sup>21</sup>

### 7.2 Which Neighborhoods Should we Target?

The consequences described above tell us about recent policy-driven expansions to the transit sector, and the heterogeneity in the impacts suggest 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 do  $\tau'_{od} = 0.9\tau_{od} \forall d$ . This is similar

 $<sup>^{21}</sup>$ As before, we use a 10% discount rate across a 50 year time horizon. Cost estimates are obtained from the Government of Medellin.

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 certain neighborhood will affect all other neighborhoods as well, as it changes criminality and formal-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 of interest. We focus on outcomes in relation to the baseline access to formal-sector opportunities.

Figure 16: Reducing Commute Costs by Each Neighborhood: P(Crime) and Rent



Notes: Scatter plots show the relationship between changes in city-level outcomes against the baseline formal-sector market access for the treated origin o, where treatment is a ten percent reduction in commute costs ( $\tau'_{od} = 0.9\tau_{od} \forall d$ ). The outcome in the left panel is the city-level criminality rate (i.e.,  $P(crime|origin)xPopulation_o)$ ). Similarly, the outcome in the right panel is the city-level rental rates.

Figure 16 has a clear message: connecting neighborhoods that have the lowest formalsector CMA at baseline are likely to lead to the largest reductions in city-level criminality, and largest increases in rental prices.

The left panel shows that in 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 an increase in city-level crime. These neighborhoods already have extremely high formal sector CMA, and so any transportation improvements there may simply allow residents to access criminal activity elsewhere in the city. As we show below, these handful of neighborhoods are in the CBD.

The right-side panel shows that rental prices increase when residents of almost any neighborhood (except the CBD) sees 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 formal-markets with the help of lower commute costs.

Figure 17: Reducing Commute Costs by Each Neighborhood: Welfare



*Notes:* Left-panel scatter plot shows the relationship between changes in city-level welfare against the baseline formal-sector market access for the treated origin o, where treatment is a ten percent reduction in commute costs ( $\tau'_{od} = 0.9\tau_{od} \forall d$ ). Right panel shows a map of the city-level welfare changes when each of the origin neighborhoods is treated with a ten percent reduction in commute costs.

Figure 17 shows the welfare consequences of these reduction in transport costs. Across almost any treated neighborhood, there is an increase in city-level welfare, and this increase is higher when areas that have less access to formal sector opportunities are treated (left panel). On the right we plot a map of city-level welfare changes for each treated origin-neighborhood. Subsidizing residents of the CBD can reduce welfare, but all other neighborhoods when treated with lower commute costs raise city-level welfare. The increase is largest for areas on the outskirts and those less connected to the transit network.

We also consider whether these patterns may be driven by the fact that a percentage reduction in commute times may produce systematically higher reductions in absolute commute times in areas with less formal market access. In Appendix Figure A.3 we show that there is no systematic pattern between the absolute change in commute times and our outcomes of interest. As such, these patterns are likely driven by access to formal-sector work opportunities.

# 8 Discussion

The spatial distribution of criminal activity and legitimate employment are interlinked by neighborhood segregation and access to different neighborhoods. Changes to transit networks meaningfully affect these relationships in a manner that can change the overall levels of crime and formal employment in cities like Medellín. Studying the impacts of expansions in transportation infrastructure is particularly important given the stark segregation of activities across neighborhoods (Kling et al., 2007; Chyn, 2018; Chetty and Hendren, 2018a; Jacob, 2004; Melnikov et al., 2019). As such, this relates to a long literature that suggests that access to economic opportunity is a meaningful determinant of criminal engagement (Becker, 1968).

We follow this tradition by studying the commuting behavior of criminals and formal workers, as it relates to economic opportunity. Doing so requires access to data on flows of workers and criminals and a robust framework to isolate the effect of transit networks on crime and formal-sector jobs. Our 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.

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# A Appendix: Additional Figures and Tables

Figure A.1: Average Homicide Arrest Rate by Destination:  $p_d$ 



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

Figure A.2: 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 A.3: 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 ( $\tau'_{od} = 0.9\tau_{od} \forall d$ ).

# **B** 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.<sup>22</sup> 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 the Google's times. The parameters of our network can be summarized on the next table.

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

Table 6: Spatial Network Calibration

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 pri-

<sup>&</sup>lt;sup>22</sup>The speed parameters for the metro system can be found here https://www.metrodemedellin.gov. co/Portals/3/Images/Contenido/REVISTAS-OTROS/2014\_nuestro-metro.pdf

vate transport travel times between 7am and 10am 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 run a linear regression using a random sample of 10263 trips between different neighborhoods obtaining an R-squared of 0.72, the results of the regression are represented on the next table:

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

Table 7: ArcGis Time vs Google Time for public transport

Total public minutes represents 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 it is our case. The following figure shows a binned scatter plot of these variables:



Figure B.4: 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.

# C 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.

### C.1 General Equilibrium

Given the model parameters { $\kappa, \theta_f, \theta_c, \eta, \beta, \alpha, \mu, \delta, \lambda, \iota, \rho, \omega$ }, the exogenous location characteristics { $B_o, B_{oc}, b_{of}, \varphi, A_c, K, \xi, \tau, p_d$ } and the reservation utility in the wider economy  $\overline{U}$ , the general equilibrium of the model is given by the set of vectors:

 $\{w_f, w_c, \theta, q, Q, \pi, A_f, B_f\}$ . In the following proposition, we show that 3N equations characterize the values of  $\{Q, w_c, A_f\}$ . The other vectors  $\{w_f, \theta, q, \pi, B_f\}$  can be written in terms of  $\{Q, w_c, A_f\}$ , the model parameters and the exogenous location characteristics.

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

$$L_{o} = \left(\frac{(1-\alpha)A_{of}}{\xi_{o}Q_{o}}\right)^{1/\alpha} H_{Eof} + \frac{(1-\alpha)}{Q_{o}}E[w|o]H_{Ro},$$

$$w_{oc} = (1-p_{o})A_{oc}H_{Eoc}^{\rho}H_{Eof}^{\iota},$$

$$A_{of} = a_{of}\left(\frac{H_{Eoc}}{L_{o}}\right)^{\lambda}.$$
(28)

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

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

Proof of Proposition 1. First notice that the variables  $H_{Eof}$ ,  $H_{Eoc}$ ,  $H_{Ro}$ , E[w|o], and  $B_{of}$  are given by  $H_{Ro} = \overline{H} \sum_{d} \sum_{s} \pi_{ods}$ ,  $H_{Edf} = \overline{H} \sum_{o} \pi_{odf}$ ,  $H_{Edc} = \overline{H} \sum_{o} \pi_{odc}$ ,  $E[w|o] = \sum_{ds} \pi_{ds|o} w_{ds}$ , and  $B_{of} = B_{oc} b_{of} \left(\frac{H_{Eoc}}{L_o}\right)^{\omega}$ . From (7), it follows that

$$H_{Ro} = B_o Q_o^{-(1-\alpha)\eta} W_o^{\eta},$$

$$H_{Edf} = \sum_o \frac{H_{Ro} B_{of} W_{of|o}^{\kappa-\theta_f} w_{df}^{\theta_f} \tau_{od}^{-\theta_f}}{WB_o},$$

$$H_{Edc} = \sum_o \frac{H_{Ro} B_{oc} W_{oc|o}^{\kappa-\theta_c} w_{dc}^{\theta_c} \tau_{od}^{-\theta_c}}{WB_o},$$

$$E[w|o] = \frac{1}{WB_o} \sum_s B_{os} W_{os|o}^{\kappa-\theta_s} \sum_d \left( w_{ds}^{\theta_s+1} \tau_{od}^{-\theta_s} \right),$$

$$B_{of} = B_{oc} b_{of} \left( \frac{A_{of}}{a_{of}} \right)^{\omega/\lambda}.$$
(29)

Here,  $W_o^{\eta} = \left(\sum_s W_{os|o}^{\kappa}\right)^{\frac{\eta}{\kappa}}, W_{os|o}^{\kappa} = \left(\sum_d w_{ds}^{\theta_s} \tau_{od}^{-\theta_s}\right)^{\frac{\kappa}{\theta_s}}, WB_o = \sum_{s'} B_{os'} W_{os'|o}^{\kappa},$   $w_{df} = \alpha \left[ (1-\alpha)^{(1-\alpha)} \frac{A_{df}}{(\xi_d Q_d)^{(1-\alpha)}} \right]^{1/\alpha},$ (30)

and  $\overline{H}\left(\frac{\gamma}{\overline{U}}\right)^{\eta} = 1$ . As a result, the system of equations given by (28) is a nonlinear system of equations of the variables  $\{Q_o, w_{oc}, A_{of}\}_{o \in \mathcal{N}}$ .

**Corollary 1.** Suppose that  $\omega \to 0$  and  $\lambda \to 0$ , then there is a unique equilibrium  $\{\boldsymbol{w}_f, \boldsymbol{w}_c, \boldsymbol{\theta}, \boldsymbol{q}, \boldsymbol{Q}, \boldsymbol{\pi}\}$ , where the crime productivities and residential amenities from the formal sector are exogenously given by  $\boldsymbol{A}_f = \boldsymbol{a}_f$  and  $\boldsymbol{B}_f = \boldsymbol{b}_f$ , 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  $\omega \to 0$  and  $\lambda \to 0$ , the endogenous crime productivities  $(\mathbf{A}_f)$  and endogenous residential amenities from the formal sector  $(\mathbf{B}_f)$  become exogenous variables. Thus, from (28), 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.

## C.2 Comparative Statics with Two Neighborhoods

To understand when reductions in transportation costs  $\tau_{od}$  will import opportunities and when it would export crime, we examine the roles played by our main parameters of interest: the sector choice parameter  $\kappa$ , the spillover externality  $\lambda$ , and transportation elasticities  $\theta_s$ . 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 formal downtown with a lot of formal 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 (28). 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  $\tau_{12}$ .

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  $B_{1c} = 4$ ,  $B_{2c} = b_{1f} = b_{2f} = 1$ ,  $B_1 = B_2 = 1$ ,  $A_{1c} = A_{2c} = a_{1f} = 1$ ,  $a_{2f} = 4$ , 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  $a_{2f} = 4$ .

Figures C.5-C.8 show the graphs of  $\{H_{Eoc}, H_{Roc}\}_{o \in \mathcal{N}}$  as functions of the transportation cost  $\tau_{12}$ , and for different values of  $\{\kappa, \lambda, \theta_c, \theta_f\}$ . 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 C.5(a) shows the graph of  $H_{Roc}$  for different values of  $\kappa$ . Recall that  $\kappa$  captures the relative labor supply elasticity across sectors: a large  $\kappa$  means that individuals tend to easily switch sectors as relative returns change. As expected, when  $\tau$  is large and, hence, neighborhoods are disconnected, there are more criminals living in neighborhood 1. As we connect this neighborhood to downtown by reducing  $\tau_{12}$ , individuals tend to switch to the formal sector as opportunity is imported. Importantly, this comparative static depends on  $\kappa$ : the larger is  $\kappa$ , the more individuals will switch towards formal employment as the relative returns of formal work increases when they are connected to productive downtown.

A decrease in  $\lambda$  (from  $\lambda = 0$  to  $\lambda = -0.147$ ), meaning larger negative externalities from crime on formal productivity, shifts  $H_{Roc}$  upward for both neighborhoods (see Figure C.6(a)). This is due to the fact that, with a large negative externality of crime on formal workers, the relative returns of formal 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.

Finally, we explore the effect of an increase in the value of  $\theta_f$  (from  $\theta_f = 3$  to  $\theta_f = 6$ ) over  $H_{Roc}$ . This parameter captures the sensitivity of formal workers to commute times. A large  $\theta_f$  implies that changes in commute costs will have a large impact on formal workers' location decisions. Note that this larger sensitivity to commute costs generates a larger sectoral shift from crime towards formal work in neighborhood one. A similar behavior can be observed as  $\theta_c$  changes (see Figure C.8(a)).

On the other hand, Figure C.5(b) shows the graph of  $H_{Edc}$ , which measures the number of criminal workers in a neighborhood, for different values of  $\kappa$ . An increase in  $\kappa$  shifts  $H_{Edc}$  downward for both neighborhoods, again, because it allows for larger sectoral changes and hence more importing of opportunity and more formal workers in the city overall. A decrease in  $\lambda$  (from  $\lambda = 0$  to  $\lambda = -0.147$ ) shifts  $H_{Edc}$  upward for both neighborhoods (see Figure C.6(b)) since larger negative externalities of crime imply that formal returns will be lower in the city overall and hence there will be smaller sectoral shifts toward that sector.



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



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

Figure C.5:  $H_{Roc}$  and  $H_{Edc}$  as functions of  $\tau_{12}$ , changing  $\kappa$ .



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



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

Figure C.6:  $H_{Roc}$  and  $H_{Edc}$  as functions of  $\tau_{12}$ , changing  $\lambda$ .



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

Figure C.7:  $H_{Roc}$  and  $H_{Edc}$  as functions of  $\tau_{12}$ , changing  $\theta_f$ .



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



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

Figure C.8:  $H_{Roc}$  and  $H_{Edc}$  as functions of  $\tau_{12}$ , changing  $\theta_c$ .