Spatial Mobility, Economic Opportunity, and Crime

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Abstract

Neighborhoods are some of the strongest determinants of both economic opportunity and criminal activity. Does improving connectedness between segregated and unequal parts of cities import opportunity or export crime? We use a 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 use new administrative data from Medellín, Colombia on the origin and destination of both workers and criminals to identify the 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 decisions of workers and criminals. Our counterfactual exercises indicate that better transit networks reduce overall criminal activity and improve welfare, despite dispersing some criminality to different parts of the city.

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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 some of the strongest predictors of 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 connect poor populations segregated from opportunity to more economically active parts of the city would reduce criminal activity. Yet, cities across the world have been resistant to such transit expansions, with the concern that crime would spread to more affluent victims and property as potential perpetrators obtain access to other neighborhoods.[1] We investigate these claims by asking: Does improving connectedness between segregated and unequal parts of cities import opportunity or export crime?

Answering this question poses numerous research design challenges. Empirically evaluating the results of these decisions on both localized and aggregate income, employment, and crime has proven 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 finding 'control groups' for comparison elusive. This is particularly exacerbated by the presence of spatial linkages and externalities across sectors and neighborhoods, and the occurrence of neighborhood specific shocks (like gang wars, and plant closings) that just happen to coincide 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 out of obtaining variation for identification purposes, and the necessary granular data. We leverage the roll out of a public transit system over a decade to identify various parameters of the model. Yet, to leverage these techniques in

[1] 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.

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

We compile different administrative data over more than a decade in Medellín, Colombia, matched across sources and time using individual social security numbers. We use the census of geocoded arrests matched to individual-level administrative records on employment and home addresses from repeated household level surveys. These new individual-level administrative data allow researchers for the first time to measure the spatial and temporal distribution of workers and perpetrators of crime. With these data, we 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 large cities in developed countries like New York, Los Angeles and Chicago. Medellin also saw 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 both decreased the likelihood that inhabitants of some poor, high crime neighborhoods were arrested for crimes, as well as increased the incidence of legitimate activity in neighborhoods that were newly connected to a fresh supply of idle "labor" in need of opportunity. 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 spatial distribution of economic opportunity in newly connected neighborhoods. For instance, the reductions in crime are most strongly seen in areas that were traditionally high-crime and segregated from other sources of legitimate economic opportunity. These countervailing patterns emphasize the importance of modeling and jointly estimating the employment decisions of individuals across both sector and space under the changing travel cost regimes.

We develop a spatial equilibrium model with both legitimate and criminal employ-

ment 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.[2]

We build on previous modeling exercises by incorporating the role of crime. Most notably, we model 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 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 a set of questions, such as: How do improvements to transportation infrastructure affect occupational choice? Does connecting poor neighborhoods to more workplace opportunities import opportunity or export crime? What are the resulting welfare effects?

To examine these, we build new cable lines that were officially proposed, but where construction was recently halted. We find that newly connected areas saw 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 was a meaningful driver of aggregate crime in the city. Despite the aggregate reductions in crime, we do find that crime was 'exported' to certain other low-crime parts of the city.

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" 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.

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

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., 2019a) and public benefits and policies (Khanna et al., 2019b; 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.[3]

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 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

[3]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.

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).[4]

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 Comercio de Medellin* (Chamber of Commerce of Medellin), which is the census of all the firms formally registered with the government in Medellín between 2007 and 2018. This database contains identification numbers of statutory representatives, total assets and liabilities reported, and most importantly, the address of establishments.

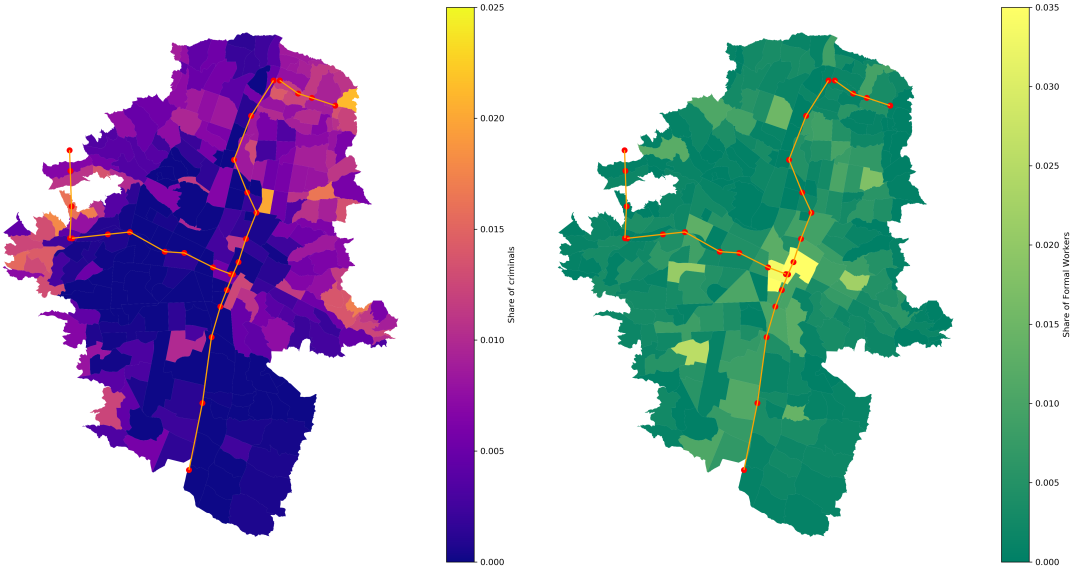
We augment these data with the Land Registry Data from the Medellin's Cadastre, which reports the use, floorspace and land area, value per square meter of land and floorspace, as well as a number of property characteristics. Finally, we obtain microdata on commuting behavior from regular mobility surveys 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 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.

[4]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.

3 Neighborhoods, Jobs and Crime in Medellín

3.1 Segregation and Urban Transit in Medellín

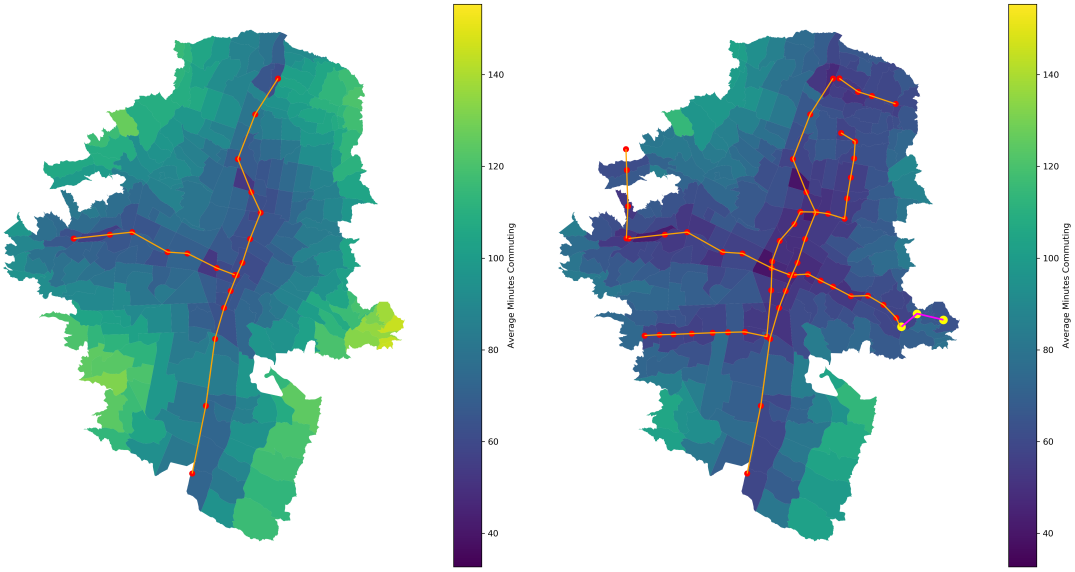
Located in the north-western region of Colombia, Medellín is the second largest city after the capital, Bogota. It has strong industrial and financial sectors with approximately 2.3 million people or 5.5% of the Colombian population. The urban zone consists of 249 neighborhoods, divided into 21 (*comunas*), 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.

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.

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.

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.

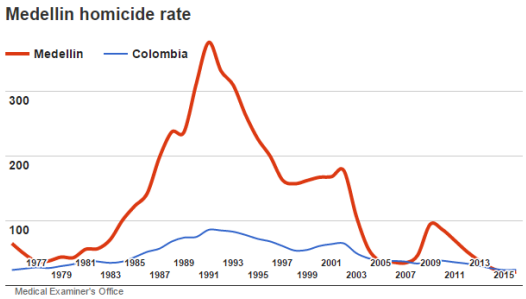
Before the roll-out of the cable car system in Medellín, most commuting relied on a single North-South metro line running through the heart of the city, at the bottom of the valley. The city displays significant elevation when moving either east or west from this central line. In order to expand the 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.

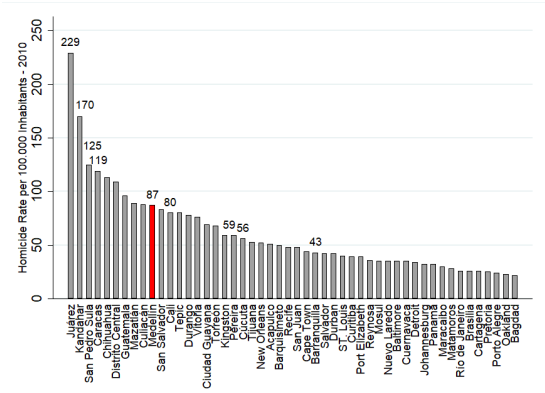
Figure 2 shows how over the period, as new transit lines were added to the city, the average commute times to various neighborhoods fell substantially, improving access to

Figure 3: Homicide Rates in Medellín Over Time, and Relative to Other Cities

(a) Homicide Rates in Medellín, 1997-2015



(b) Highest Homicide-rate Cities, 2010



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

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.[5] 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

[5] *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).

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 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.[6] 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.[7] Indeed, the options are often presented as an occupational choice: "*are you gonna work [for the gang] or do a normal job?*"[8]

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 earnings "put them in the top 10% of income earners in the city."[9]

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

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

[7]See *interview with El Peludo, p184.*

[8]See *interview with Notes, p193*

[9]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.

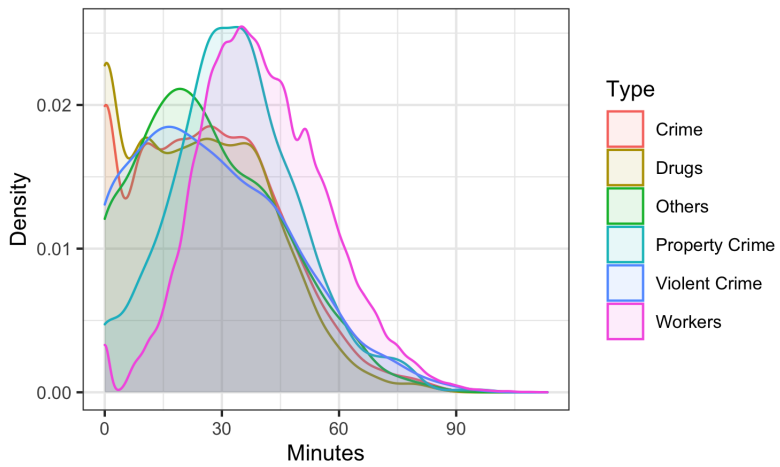
are committed by offenders under the age of 30, and 72% by males (Kearney et al., 2014). Accordingly, in some regards, arrests in our context are similar to high-crime regions in many parts of the developing world, and especially Latin America (Dell et al., 2018).

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.

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.

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.

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:

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

Here, γ_t are time fixed effects that control for changes in aggregate crime and transportation across neighborhoods, and γ_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, β_1 is the DiD estimator for the effect of being further away from a newly built cable station on crime.

Yet, this β_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:

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

Table 1: The Effects of New Cable Lines on Crime

	Effects on Destinations		Effects on Origins	
	Any Crime	Violent Crime	Any Crime	Violent Crime
Log(Distance to Station)xPost	0.0970**	0.180***	0.0693***	0.154***
	(0.0438)	(0.0523)	(0.0232)	(0.0316)
Observations	3,486	3,416	3,192	2,996
Data Structure	Destination-by-Time		Origin-by-Time	
Destination Fixed Effects	Yes	Yes	No	No
Origin Fixed Effects	No	No	Yes	Yes
Origin-Destination Distance	No	No	No	No
Time Fixed Effects	Yes	Yes	Yes	Yes
SE Cluster	Dest	Dest	Origin	Origin

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 origin-by-destination-by-time level, we can control for time invariant features of the origin-

destination pair, such as the distance between them Ξ_{od}, along with time invariant features of destinations γ_d and origins γ_o.

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

Here, β_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.

Table 2: The Effects of New Cable Lines on Crime

	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			

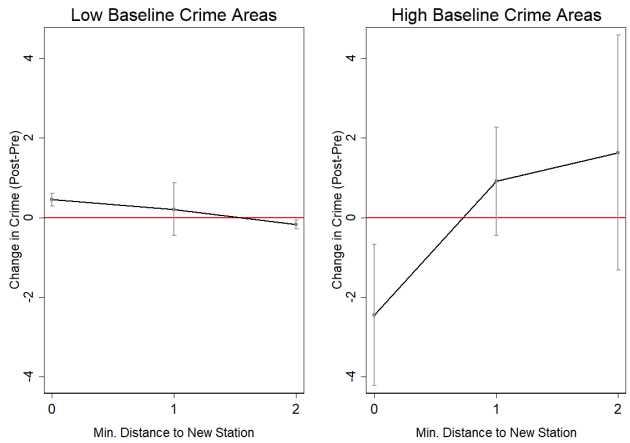
Notes: The first two columns show difference-in-differences estimates for being close to a station, and crime destinations. The last two columns show the effects on origins (residences) of crime perpetrators. The data are at the origin-by-destination-by-year level.

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 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

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.

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 are connected to the cable line, crime may fall, as youth from these neighborhoods can easily access legitimate activity in other parts of the city.

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 the left panel of 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.

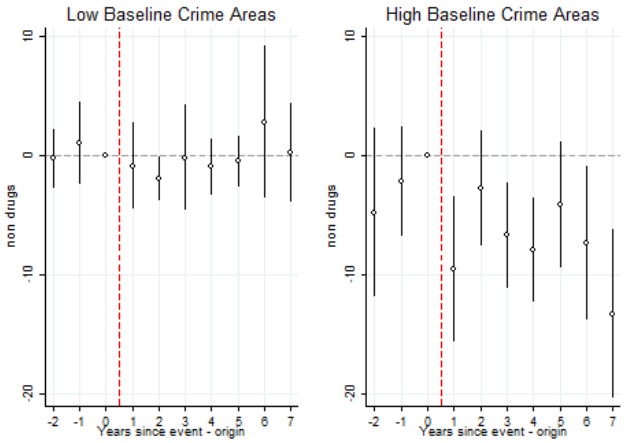
4.4 Event Study Analyses

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 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

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.

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 – by exploring 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.

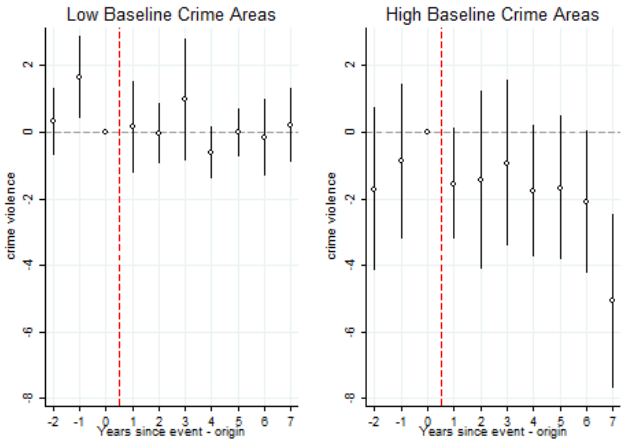
Finally in Figure 8, we restrict our sample to only low income neighborhoods, and compare the differences in magnitudes between the violent and the non-drug crimes. The effects on non-drug crimes are a lot larger than the effects on just violent crime.

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

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.

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

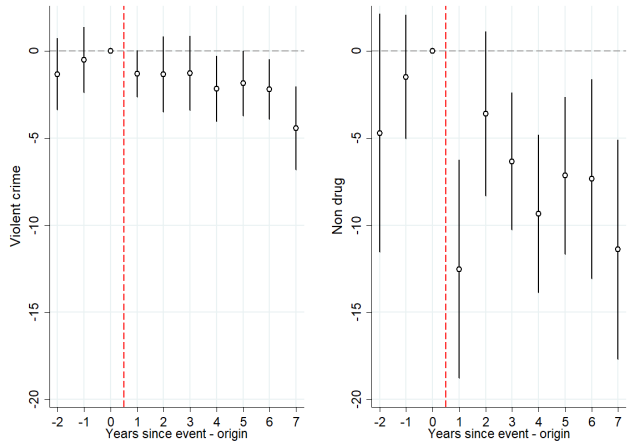
$$Log(Crimes)_{ot} = \gamma_t + \gamma_o + \beta_3 Minutes\ to\ Station_{ot} + \epsilon_{3ot} \tag{4}$$

Here, the identification of β_3 comes only from changes over time in the travel-time to the closest station, as and when new lines are built, once again conditional 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, 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:

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

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.

Table 3: The Effects of Travel Time to Station

Travel Time To Station	In Origin	In Destination	In Origin	In Destination
	Any Crime		Any Crime	
Minutes to Station	0.00183**	0.00519*	0.00192*	0.00537**
	(0.000915)	(0.00268)	(0.00108)	(0.00274)
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	

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.

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* 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 θ_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-by-destination-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 γ_{ot} and destination by time fixed effects γ_{dt}:

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

We return to Equation 6 later in our analysis as it helps causally identify the crucial parameters of our model. Here, γ_{ot} and γ_{dt} account for neighborhood-by-time level shocks, such as new gang wars, or changes policing that change over time by neighborhood. Ξ_{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 β_4 is meaningfully informative of crucial economic elasticities that drive the spatial distribution of crime and legitimate activity across the city.

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

Travel Time From Origin To Destination	Any Crime	Violent Crime	Formal Work
Minutes From Origin to Destination	-0.0791***	-0.0755***	-0.0138***
	(0.00364)	(0.00406)	(0.00126)
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	

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.

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 β_4 causally inform our model's parameters.

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 $\bar{H}$ 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 ω 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, ϵ_{ods}.[10]

[10] 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.

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 ϵ_{ods} is drawn from a nested Frechet distribution:

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

Given the observed shocks, individuals decide where to reside, which sector to work in, and where to work. The parameters η, κ, θ_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 $W_{os|o}^{\theta_s} = \sum_{d'} w_{ds}^{\theta_s} \tau_{od}^{-\theta_s}$ is an origin-sector specific wage index.[11]

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 commute-discounted 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 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 $\bar{U}$. Thus, spatial equilibrium requires expected utility equaliza-

[11] The nested frechet assumption allows us to decompose the overall probability of choosing an origin-sector-destination into three different components. $\pi_{ods|os}$ the probability of choosing a destination 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 $\sum_d \pi_{ods|os} = \sum_o \pi_{os|o} = \sum_o \pi_o = 1$.

tion:

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

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:

$$y_d = A_d \left(\tilde{H}^w_{fd}\right)^{\alpha} (L_{fd})^{1-\alpha} ,$$

where A_d is final goods productivity, $\tilde{H}^w_{fd}$ is workplace formal employment, and L_{fd} is commercial floorspace in destination d.

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_d, 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:

$$q_d = (1-\alpha)\left(\frac{\alpha}{w_d}\right)^{\alpha/(1-\alpha)} A_d^{1/(1-\alpha)} \tag{9}$$

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:

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

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:[12]

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

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:

$$\mathbb{E}[\ell_{ods}|o]\tilde{H}_o^r = (1-\theta_o)\, L_o \ , \tag{11}$$

where $\tilde{H}_o^r$ 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:

$$\left(\frac{(1-\alpha)A_d}{q_d}\right)^{1/\alpha} \tilde{H}_{fd}^w = \theta_d L_d \tag{12}$$

5.2 Criminal Sector and its Effect on Productivity

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

$$w_{dc} = (1-p_d) A_{dc} H_{dc}^{\rho} H_{df}^{\iota} \tag{13}$$

where $\rho \in [-1, 0]$ and $\iota \in [0, 1]$, where H_{dc} and H_{df} are total number of criminals and total number of formal workers in d. This specification captures congestion forces of

[12] 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.

multiple criminals commiting crimes in the same destination through ρ 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.[13]

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_d, at destination d is given by:

$$A_d = a_d \Upsilon_d^{-\lambda} \ ,$$

where $a_d > 0$ is the fundamental and exogenous component of productivity, and Υ_d is a function that captures negative spillovers of crime to productivity in the formal sector in destination d. $\lambda \in [0, 1]$ is a parameter that captures how important these negative spillovers are for the formal sector. We model these negative externalities spatially as:

$$\Upsilon_d \equiv \sum_{k=1}^{D} e^{-\nu \tau_{dk}} \frac{\tilde{H}_{kc}^{w}}{K_k} \ , \tag{14}$$

where H_{kc} is the total number of criminals in destination k, K_k is total land area in destination k, ν is a parameter that captures how relevant crime at different distances is for productivity, and τ_{dk} are the iceberg commuting costs between blocks d and k.

5.3 Equilibrium

Given model parameters $\{\kappa, \theta_f, \theta_c, \eta, \beta, \alpha, \mu, \delta, \lambda, \iota, \rho\}$, the reservation utility in the wider economy $\bar{U}$, vectors of exogenous location characteristics $\{\mathbf{B_o}, \mathbf{B_{os}}, \boldsymbol{\varphi}, \boldsymbol{A}_f, \boldsymbol{K}, \boldsymbol{\xi}, \boldsymbol{\tau}, \boldsymbol{A}_c, p_d\}$ the general equilibrium of the model is given by the vectors $\{\boldsymbol{w}_f, \boldsymbol{w}_c, \boldsymbol{\theta}, \boldsymbol{q}, \boldsymbol{Q}, \boldsymbol{\pi}\}$, 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.

[13] 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.

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_{od} 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, γ_{ot} are origin-time fixed effects, γ_{dt} are destination-time fixed effects, ϵ_{odst} captures measurement error observed in the data.

Our goal is to recover the parameters θ_s after knowing β_s and δ_d. We estimate this equation via PPML to include zero commuting flows between municipalities.

6.2 Labor Supply Elasticity Sectors

We now discuss how we recover κ, which corresponds to the labor supply elasticity across sectors that governs the reallocation of workers from the criminal sector to the formal economy. As in Tsivanidis (2018), we define the **sector-specific commuter market access (CMA)** for location n, sector s as:

$$\text{CMA}_{os} \equiv \sum_{d} w_{ds}^{\theta_s} \tau_{od}^{-\theta_s} \ , \tag{15}$$

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:

$$\text{FMA}_{ds} \equiv \sum_{o} \frac{\tau_{od}^{-\theta_s}}{\text{CMA}_{os}} \tilde{H}_{os}^{r} \ ,$$

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:

$$\text{CMA}_{os} = \sum_{d} \frac{\tau_{od}^{-\theta_s}}{\text{FMA}_{ds}} \tilde{H}_{ds}^{w} \tag{16}$$

$$\text{FMA}_{ds} = \sum_{o} \frac{\tau_{od}^{-\theta_s}}{\text{CMA}_{os}} \tilde{H}_{os}^{r} \ , \tag{17}$$

where $\tilde{H}_{ds}^{w}$ represents the total amount of workers in location d sector s, $\tilde{H}_{os}^{r}$ 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.

Since we intend to identify κ off of variation across time in exogenous formal sector firm productivity (as we explain below), we derive an estimation equation using:

$$\frac{H_{of,t}}{H_{oc,t}} = \left(\frac{[\text{CMA}_{of,t}]^{1/\theta_s} \, \Gamma(\frac{\theta_f - 1}{\theta_f})}{[\text{CMA}_{oc,t}]^{1/\theta_s} \, \Gamma(\frac{\theta_c - 1}{\theta_c})} \right)^{\kappa} \ ,$$

where $\Gamma(\cdot)$ is the gamma function. Taking logs, we obtain:

$$\ln H_{of,t} - \ln H_{oc,t} = \kappa \left(\frac{1}{\theta_f} \ln \text{CMA}_{of,t} - \frac{1}{\theta_c} \ln \text{CMA}_{oc,t} \right) + \kappa (\ln \Gamma(\frac{\theta_f - 1}{\theta_f}) - \ln \Gamma(\frac{\theta_c - 1}{\theta_c})) \tag{18}$$

where $H_{of,t}$, and $H_{oc,t}$ correspond to the total number of residents that live in location n and work in formal and crime sectors.

Equation 18 is a relative labor supply relationship which implies that people reallocate to the formal sector as they obtain better access to formal jobs relative to informal employment, with an elasticity κ. From equation 18, we arrive at the following estimation equation:

$$\ln H_{of,t} - \ln H_{oc,t} = \kappa \left(\frac{1}{\theta_f} \ln \text{CMA}_{of,t} - \frac{1}{\theta_c} \ln \text{CMA}_{oc,t} \right) + \gamma_o + \gamma_t + \epsilon_{ot} \ , \tag{19}$$

where γ_o and γ_t are origin and time fixed effects, respectively.

Identification Given that equation 18 expresses a labor supply relationship, there is an endogeneity concern when estimating κ. $\ln H_{of,t} - \ln H_{oc,t}$ and $\frac{1}{\theta_f} \ln \text{CMA}_{of,t} - \frac{1}{\theta_c} \ln \text{CMA}_{oc,t}$ will be correlated due to shifts of the relative labor supply curve in addition to shifts along the relative labor supply curve. κ, as an elasticity, is meant to describe shifts along the curve. If we include variation from shifts of the entire relative labor supply curve, our estimate of κ will be biased.

To address this, we estimate the specification in equation 18 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 supply curve. Thus, our LATE will reflect only variation from shifts along relative supply, allowing us to identify κ.

Note, that these Bartik instruments will correspond to *destinations* in our data, whereas equation 18 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 16 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.

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

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 $W_{ot} = (\text{CMA}^{\kappa}_{oc,t} + \text{CMA}^{\kappa}_{of,t})^{\frac{1}{\kappa}}$. 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), γ_t is a time-fixed effect, and ϵ_η is the error term. We need an instrument for $(\ln W_{ot} - (1-\beta)\ln Q_{ot})$ to identify η 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 $\text{CMA}_{of,t}$ and not the residential amenity.

6.4 Crime Externality

To estimate the crime externality parameters (ν, λ), 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 $\Upsilon_{dt} = \sum_{k=1}^{D} e^{-\nu\tau_{dk,t}} \frac{\tilde{H}^{w}_{kc,t}}{K_k}$:

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

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

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

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 Δ 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:

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

where $h(Z)$ is the vector of instruments discussed below. We implement estimation of the crime externality parameters using GMM.

Identification Like Ahlfeldt et al. (2015) , we want to identify (ν, λ) using only variation coming from changes in commuting access and the resulting change in the crime externality rather than other reasons for changes in $\Delta log(\frac{a_{dt}}{\bar{a}_t})$ (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 λ, and variation within the same distance band and correlated with differences in commuting time help us identify the iceberg spillover ν.

6.5 Other Parameters

We take some parameters from the literature. Specifically, $(1-\beta), (1-\mu), (1-\alpha)$, which are, respectively, the share of residential floor space in consumer expenditure, the share of land in construction costs, and the share of commercial floor space in firm costs. These are set following Ahlfeldt et al. (2015) to $\alpha = 0.8$, $\mu = 0.75$, $\beta = 0.75$.

For the time disutility parameter δ 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 use the parameters from Ahlfeldt et al. (2015) $\nu = 0.3585, \lambda = 0.0793$.

For the sectoral choice parameter, we set it to $\kappa = 1.2$, while for the migration elasticity we set it $\eta = 1.1$ close to the value estimated by Tsivanidis (2018).

6.6 Model Inversion

Given the value of the parameters, we can recover the fundamentals of the model $\{B_{os}, A_d\}$.[14] In order to do so, we first solve for commuter and firm market access given observed residential and labor decisions through equations 16 and 17.

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

Given the recovered $\{\text{CMA}_o, \text{FMA}_o\}$, one can obtain the model-implied wages from the sectoral labor supply equation:

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

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:

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

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:

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

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

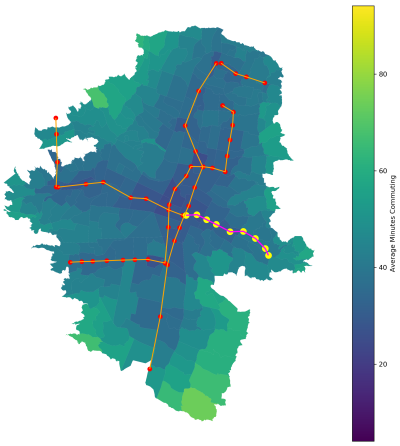
What are the sectoral choice effects of transportation infrastructure investments? Does connecting poor neighborhoods to the Central Business District (CBD) import opportunity or export crime? What are the resulting welfare effects? We answer these questions through the lens of the model focusing on two counterfactuals motivated by public policy. First, we evaluate the welfare effects of a tram line built in 2016 by the government in Medellin. We then evaluate the welfare effect of a new cable line that is currently under construction and is projected to be inaugurated by the end of 2020.

7.1 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.

Importantly, these were relatively poor neighborhoods where criminals tended to live.

Figure 9: Tram line Built in 2016

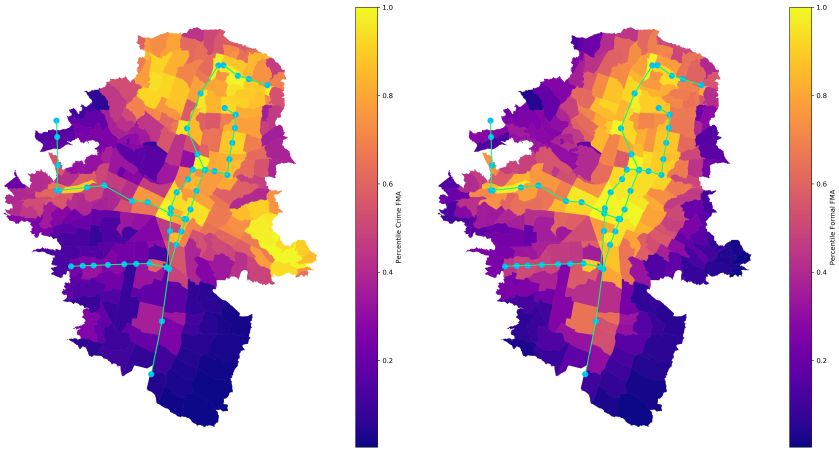


Notes : This map shows the average minutes of commute by neighborhood of origin across destinations. The pink line shows the tram that was built in 2016.

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.

Figure 10: Sectoral Firm Market access, 2015

(a) Crime Firm Market access (b) Formal Firm Market access



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

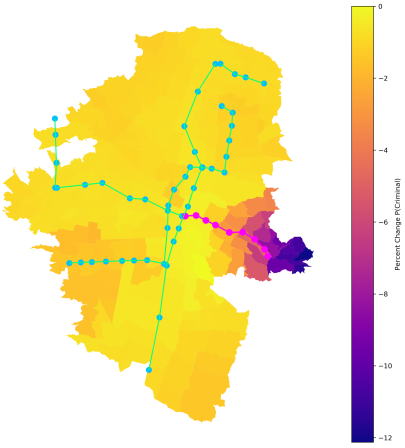
Ex-ante, the effect of connecting these neighborhoods to the CBD on individuals' sector choice is ambiguous. on the one hand, reducing commute costs to the CBD increases

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 the model for the endogenous variables.[15] 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.

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



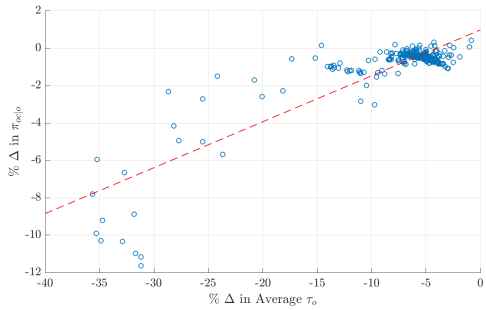
Notes : The map shows the model implied percent change in the probability of becoming a criminal conditional on origin, $\pi_{oc|o}$ across neighborhoods of origin, given the change in commute costs.

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

[15] 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.

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.

Figure 12: Relationship Between Change in Commute Cost and Sector Choice



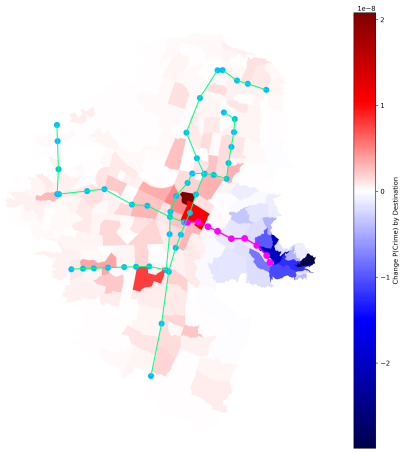
Notes : The scatterplot shows the relationship between the percent change in average commute costs at the origin level and the percent change in the probability of becoming a criminal at the origin level as well.

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 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.

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%.

Figure 13: Change in Probability of Commiting a Crime by Destination

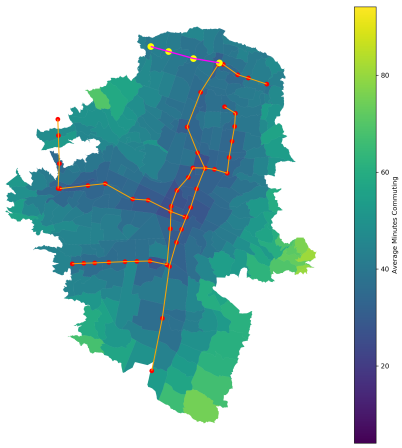


Notes : The map shows the model implied change in the probability of committing a crime by destination conditional on living in the easternmost neighborhood, $\pi_{odc|oc}$, across destinations.

7.2 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.

Figure 14: Cable line Under Construction in 2020



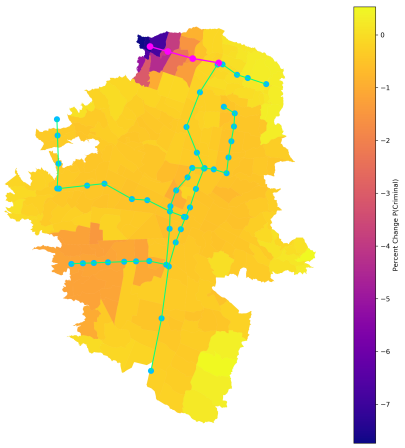
Notes : This map shows the average minutes of commute by neighborhood of origin across destinations. The pink line shows the cable line that is projected to start operations by the end of 2020.

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, 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, the investment in the new cable line had a smaller and more geographically concentrated impact on the probability of becoming a criminal.

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.

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.[16]

Finally, we evaluate the change in expected welfare due to the construction of the new cable line assuming that there is no in nor out-migration from 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.

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. Yet, examining such relationships require access to data and a robust framework that allows us 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 changes to opportunity access affects the levels of criminal activity, but also the geographic spread of such activity to different neighborhoods. Our examination suggests that improving the access to jobs in different parts of the city can substantially lower crime rates in such high-crime environments. Yet, criminal activity may spread to different neighborhoods as a result of connecting segregated regions.

These results are particularly strong given the segregation in different 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.

[16]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.

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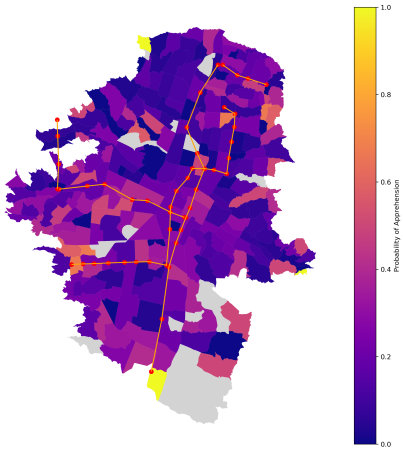
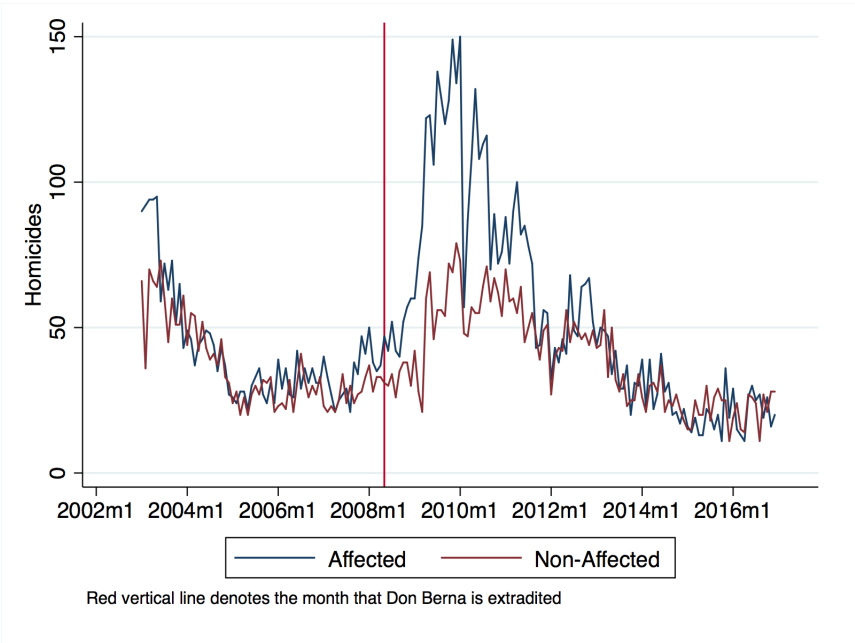
A Appendix: Additional Figures

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



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

Figure 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.