Flight from Urban Blight:
Lead Poisoning, Crime and Suburbanization

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Abstract

In the post World War II period, most U.S. cities experienced large movements of population from the city centers to the suburbs. In this paper we provide causal evidence that this process of suburbanization can be explained by the rise of violent crime in city centers. We do so by proposing a new instrument to exogenously predict violent crime. This instrument uses as time variation the U.S. national levels of lead poisoning. Cross-sectional variation comes from a proxy for soil quality, which explains the fate of lead in soil and its subsequent bioavailability. Using data for more than 300 U.S. cities, results show that the increase in violent crime from the level in 1960 to its maximum in 1991 decreased the proportion of people living in city centers by 15 percentage points. This increase in crime moved almost 25 million people to the suburbs. As a result of suburbanization, we find that people remaining in the city center are more likely to be black people, consistent with the "white flight" phenomenon. We then demonstrate that this suburbanization process had aggregate effects on the city. Exploiting a spatial equilibrium model, we determine that violent crime had externalities on productivity and amenities.

1 Introduction

In the last century, both developed and developing countries experienced at the same time two important urban phenomena: urbanization and suburbanization. Urbanization refers to the movement of people from rural to urban areas. Suburbanization represents the movement of population from city centers to low density suburban areas. The increase in the number of people living in the suburbs is not just caused by city growth, as shown by Angel et al. (2011). U.S. cities provide an emblematic example of this suburbanization process. According to Baum-Snow (2007), U.S. population living in city centers declined by 17 percent between 1950 and 1990 despite population growth of 72 percent in metropolitan areas.

The advantages and drawbacks of city growth have been largely studied. Urbanization reflects agglomeration economies and higher productivities. At the same time, large cities might suffer congestions and urban distress. In particular, crime is higher in bigger cities (Glaeser and Sacerdote, 1999). The movement of people from city centers to suburbs can underline the negative effects of density. In this paper we provide novel causal evidence for a mechanism that links the increase in violent crimes in U.S. city centers between the 1960s and the 1990s to suburbanization. We then show the consequences of this reallocation of people within cities in terms of racial segregation, and overall city productivity and amenities. Suburbanization of people has implications in terms of congestions and transport costs, decreasing amenities in cities. It also affects location of firms and then city productivity. Therefore, in this paper we show that suburbanization is crucial to explain how city structure can influence productivity and amenities externalities offered by cities, something that has received the attention of a limited number of studies.

While in 1960, 43% of the urban population in the U.S. was living in city centers, this proportion dropped to 33% in 1990. In this paper, we argue that the amenity value of city centers in the U.S. decreased because of crime, leading people to suburbanize. In fact, U.S. cities experienced a dramatic increase in violent crimes at the same time that population suburbanized (see Figure 1(a)). The violent crimes rate rose from 23 crimes per 10,000 inhabitants in 1960 to 163 crimes per 10,000 inhabitants in 1991. Similarly, cities in which violent crime increased the most had the strongest decrease in proportion of people living in city centers (see Figure 1(b)). When crime rates decreased, after 1991, the general trend for suburbanization did not revert.[1]

[INSERT FIGURE 1 HERE]

The goal of this research is to provide causal evidence and to quantify the effect of crime on suburbanization. We do so by proposing a new instrument to exogenously predict violent crime rate in the city centers of all U.S. cities. The time variation of our instrument is provided by U.S. national levels of lead consumption. Medical literature recognizes that exposure to lead as a child alters the formation of the brain and increases aggressive behaviour in adulthood. We exploit the specific timing of the effect of lead on crime to be sure that we are not capturing the effect that lead might have on other outcomes. Lead emissions by cars in the U.S. increased dramatically

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[1]There are some recent studies that provide evidence of the return of some categories of population to city centers, in particular white people with college degree (see Baum-Snow and Hartley, 2016 for a review). However, these individuals represent a small proportion of the U.S. population.

until 1972, and 19 years later crime rates reached their peak. Given that our identification strategy takes advantage of this increase in lead exposure, we concentrate our analysis on the period between 1960 and 1991. Lead emissions by cars accumulate in the soil and then can be ingested by humans via soil resuspension. We obtain geographical variation for our instrument by exploiting the chemical literature evidence showing that lead bioavailability to humans increases when lead deposits in soils of a particular pH level. We use this information to instrument violent crime rates using the interaction between the lagged national level of tetraethyl lead used in cars and a function of the pH of the soil. We construct this instrument using machine learning techniques as described in Section 4.2.

We estimate the effect of violent crime on suburbanization using a newly assembled database for more than 300 U.S. cities. Our results show that the increase in violent crimes from the level of 1960 to their maximum in 1991 was responsible for a decrease in the proportion of people living in city centers by 15 percentage points. Increases in violent crime led more than 25 million people to leave city centers. However, we encounter that the increase in crime rate did not change the total city population. Higher crime rates in the city centers drove people to relocate within cities but not between cities. We also find that this suburbanization process was associated with the so-called "white flight". As a city center became more violent, white people moved to the suburbs, leading to an increase in the percentage of black people in the city center. Moreover, we provide evidence that the increase in violent crime was not only responsible for residential suburbanization but also it induced firms to leave city centers and locate in the outskirts of the city. Employment decentralization followed residential suburbanization and not the opposite. These results are confirmed after several robustness and specification tests.

After showing that violent crime had an effect on the distribution of people and firms inside a city we explore whether this phenomenon generated aggregate effects at the city level. In addition to finding that violent crime did not decrease the overall population of the city, we prove that violent crime increased both house prices and median incomes. To rationalize these city-aggregate results, we estimate a spatial equilibrium model, based on Glaeser (2008), in which people decide in which city to locate and in equilibrium utility should be equalized between cities. We assume that violent crime can affect city amenities and productivity. We exploit the model to map reduced form elasticities of the effect of violent crime on house prices, wages and total city population, to structural parameters that describe the effect that violent crime has on city amenities and productivity. We find that higher violent crime rates and the consequent relocation of people inside a city decrease city amenities but increase overall city productivity. Our structural estimates imply that the increase in violent crime in the city center between 1960 and 1991 led to a decrease in the average amenities of the city of 23.2%. We provide suggestive evidence that the effect of crime on productivity is entirely caused by the effect that crime has on employment decentralization.

This paper first contributes to the literature about the determinants of suburbanization. Several reasons have been identified as contributors of the suburbanization of U.S. cities. Causal evidence of the effect of highways on suburbanization has been

provided by Baum-Snow (2007).[2] Brueckner and Rosenthal (2009) argue that suburbanization is explained by the fact that high-income households have higher demand for newer housing stock, which develops faster in suburban locations. Boustan (2010) shows that the large migration of black population from the rural South of the U.S. led to whites leaving the cities. Reber (2005) provides evidence that white flight has been stronger in districts with court-ordered desegregation plans.[3] Several early studies have more generally related urban blight to the flight from city centers.[4]

We show that the increase in crime rates from the 1960s to the 1990s is an important reason for U.S. suburbanization. According to our estimates, the relative increase in crime between city centers and suburbs from 1960 to 1991 implies a 35% decrease in the population of city centers. We can compare this result to similar numbers in the literature. Baum-Snow (2007) provides evidence that the construction of the interstate highway system reduced the population of city centers by 23%. The effect of the great black migration has been estimated to cause a drop in 17% in city center population (Boustan, 2010). In this paper, we demonstrate that the effect of violent crime has important complementarities with these other mechanisms. In fact, we show that the increase in violent crime rates increased the construction of highways and decreased the white population in the city centers, which consecutively further influenced suburbanization. We also find that the suburbanization caused by crime is stronger in cities with more blacks in the city center and in cities with more highways.

The link between crime and relocation of people has been the object of study of a limited amount of analyses. Cullen and Levitt (1999) were the first to causally consider the relationship between crime rates and city population. Their empirical strategy consists of analyzing the effect on a city center population of crime rates instrumented by the lagged changes in the punitiveness of the state criminal justice system and controlling for city and year fixed effects and several city characteristics. They conclude that the decrease in city population because of increased crime rates is mainly due to people migrating out of the city center. Our work differs from Cullen and Levitt (1999) because we exploit exogenous variation at a much finer geographical level of observations that do not correlate with any potential suburbanization confounding mechanism at city level.

Our findings relate to the growing literature on optimal city structure. These studies rely on the classical urban models developed by Alonso (1964), Mills (1972), and Muth (1969), and subsequently expanded by Fujita and Ogawa (1982), Lucas and Rossi-Hansberg (2002), Ahlfeldt et al. (2015), and Allen et al. (2015). Our work also connects to studies about how urban amenities change in response to urban shape and crime. The cornerstone of these works is the spatial equilibrium concept introduced by the seminal works by Rosen (1979) and Roback (1982), and then reviewed by Glaeser (2008) and Moretti (2011). Similar to our work, Harari (2015) estimates the externality effects of urban compactness. Diamond (2016) shows that crime is an

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[2]Similar evidence has been found for the case of Spain (Garcia-Lopez et al., 2015) and other European countries (Garcia-Lopez et al., 2015). Similarly, Glaeser and Kahn (2004) and Kopecky and Suen (2010) relate suburbanization to car adoption.

[3]This last result was not confirmed by Baum-Snow and Lutz (2011) who find that school desegregation affected only out-of-city migration and not within-city suburbanization.

[4]See, for example, Bradford and Kelejian (1973), Frey (1979), Grubb (1982), Mieszkowski and Mills (1993), and Mills and Lubuele (1997). Cullen and Levitt (1999) look specifically at the role of crime.

important component of urban amenities, which then influences location of people. We contribute to these literatures by showing that the effect of crime on employment decentralization creates externalities over city amenity and productivity.

Our paper also contributes to a long-standing stream of literature that studies the determinants of violence and crime.[5] In particular, we relate to the strand of this literature that studies the biological determinants of violence. As reviewed by Rowe (2002) and O'Flaherty and Sethi (2015) there is a growing body of evidence on how genetic, medical and environmental factors may increase the propensity of violent behavior. In particular, we build on a medical literature that has shown how lead poisoning is a potent neurotoxin that is closely related to aggressive and violent behavior. In economics, there is a new and growing stream of literature that studies the relationship between lead poisoning and crime (see Section 4.1 for a review of the literature). We contribute to this literature by exploiting a new source of cross-sectional variation given by the type of soil in a city. We then use this new instrument to provide causal evidence of the effect lead poisoning from resuspended lead has on violent crime.

Moreover, we contribute to the literature that studies the effects of crime. Here, the literature has mainly focused on the detrimental effects that a violent environment has on the young, especially when it comes to their educational decisions (Bowen and Bowen, 1999; Henrich et al., 2004). Another important strand of the literature has instead looked at the effects crime has on economic activity, mainly by deterring investments (Daniele and Marani, 2011; Detotto and Otranto, 2010). In this paper, we provide causal evidence of the effects that crime has on suburbanization and how this shapes the location of people inside a city.

Finally, our work is one application of machine learning for construction of instrumental variables (see Athey and Imbens, 2017 for a review). We select a proxy of soil quality between a large set of possible alternatives using an algorithm that finds the instrument that maximizes the relevance condition. We run the first stage of our regression for any possible interval of soil pH and we select the interval that maximizes the F-statistics. We then show how the pH of the soil selected by this algorithm conforms to what is expected by the chemical literature. We argue that the soil quality index selected is in line with the identification assumption required for exogeneity and we show that the results are robust to the use of other proxies.

This paper is structured as follows. Section 2 discusses the empirical strategy to obtain the causal effect of crime on suburbanization. Section 3 describes the data used. The instrumental variable and the identifying assumptions are explained in Section 4. Empirical results are reported and discussed in Section 5. Section 6 examines the possible threats to identification and provide evidence of the robustness of the results. In Section 7, we present the spatial equilibrium model and estimates of the externality effects of crime rates on amenities and productivity. Lastly, Section 8 concludes.

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[5]Most of the efforts in this literature have been concentrated in assessing the effect of police, incarceration and the judicial system on the criminal activity (for the most recent literature review, see Chalfin and McCrary, 2017). Another strand of the literature instead has been focused on how different social and economic circumstances may affect crime. Examples of these determinants are income inequality (Kelly, 2000), immigration (Bianchi et al., 2012), gun laws (Ludwig, 1998) and social cohesion (Goudriaan et al., 2006) among many others.

2 Empirical strategy

The empirical model we want to estimate is reported in Equation 1. Our objective is to understand the effect of the increase in violent crimes per capita (*VC*) in the city center (*cc*) of one metropolitan area (*m*) in a particular year (*t*) on the suburbanization of that city. The proxy for suburbanization ($sub_{m,t}$) we use is the proportion of population living in the city center (pop^{cc}) over the total city population, which is the sum of the population in the city center and in the suburbs (pop^{ncc}). In order to control for unobserved heterogeneity we introduce both metropolitan area (MSA) and year fixed effects, τ_m and τ_t, respectively. We also include geographic (g) specific time trends, i.e. $\tau_g \times \tau_t$. In our preferred specification we impose Census District time trends (discussion of these time trends is presented in Section 4.3).

$$sub_{m,t} = \frac{pop^{cc}_{m,t}}{pop^{cc}_{m,t} + pop^{ncc}_{m,t}} = \tau_m + \tau_t + \beta VC^{cc}_{m,t} + \tau_g \times \tau_t + \varepsilon_{m,t} \tag{1}$$

The OLS estimation of the coefficient of the effect of violent crime on suburbanization, β can suffer different biases. Firstly, reverse causality might be present since more suburbanized cities might have poorer city centers, which in turn can increase crime rates in the city center. Evidence of this reverse causality has been found by Jargowsky and Park (2009). Moreover, omitted variable biases can contribute to the inconsistency of our estimation. One possible omitted variable is the proportion of black people living in the city center. Boustan (2010) shows that part of the white flight has followed the influx of black population in the city. This estimation can also suffer omitted variable bias if cities with more highways tend to have higher level of crimes.

We propose a new instrument that, we argue, can exogenously predict crime at city center level: the interaction between the lagged amount of the tetraethyl lead (TL) used in car gasoline in the U.S. and a proxy for the bioavalability of lead to humans in the ciy centers. Lead has an effect of brain development of children, and increase their aggresive behaviour. The highest potential of delinquency is reached at 19 years old.[6] Hence, for any given year, we use tonnes of tetraethyl lead in cars 19 years before to predict crime rates. Section 4.1 discusses in details the relationship between lead and crime.

Lead adsorption in the soil depends on particular soil characteristics. Bioavailability of lead is proxied by a specific function of the average pH of the soil in the city center. In particular, our soil bioavailability indicator is a dummy variable taking value 1 if the average pH of the soil is between the values of 6.8 and 7.7. We obtain this proxy using a machine learning algorithm described in Section 4.2. The first stage of our instrumental variable estimation is reported in Equation 2. One of the main advantages of our instrument is that it varies both in space and time, therefore we can include year and city fixed effects in our first stage.

$$VC^{cc}_{m,t} = \mu_m + \mu_t + \chi TL_{t-19} \times \mathbb{1}\left(6.8 \leq pH^{cc}_m \leq 7.7\right) + \mu_g \times \mu_t + \epsilon_{m,t} \tag{2}$$

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[6]According to United States Department of Justice (1993) in 1965 people with 19 years old had the highest arrest rates for violent crimes.

3   Data

We have assembled an unique database for 306 city centers from 1960 to 2014 in the U.S. combining different data sources. The first data source we use is the F.B.I. Uniform Crime Reporting (UCR) Program Data (United States Department of Justice). For each local enforcement agency, which is coded by a Originating Agency Identifier (ORI) number, this data source provides information about monthly number of crimes for each year for all different kind of crimes.[7] This database also reports the total jurisdictional population under responsibility of that particular ORI. We use this information to compute our suburbanization measure.[8] We use the F.B.I. definition of violent crime, that is the sum of murder and non-negligent manslaughter, total robberies, forcible rape, and aggravated assaults.[9] We use the Law Enforcement Agency Identifiers Crosswalk database to link ORIs to Census Geographic Definitions (National Archive of Criminal Justice Data, 2006). We keep geography fixed at 2000 definition and we aggregate all the information at U.S. Place level.[10]

We merge our database with the data provided by Baum-Snow (2007). This database contains information of several social and economic characteristics of Metropolitan Statistical Area (MSA) and city centers.[11] Moreover, we use the definition of city centers provided by Baum-Snow (2007), that is for each MSA he defines the city center as the U.S. Place with the largest population in 1950.[12] Therefore, for every city center we can compute its jurisdictional population, the population of the rest of places inside the same MSA (that we call suburbs) and the population of the MSA. The suburbanization measure we use is the population in the city center divided by the population in the MSA. Similarly, we construct violent crime rate per capita at city center, suburb, and MSA level.

For the construction of our instrument we use two different databases. First, we use the United States Geological Survey (U.S.G.S.) General Soil Map in order to obtain

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[7]We aggregate monthly data to years data. If crimes were not reported for more than 9 months we reweight the number of crimes by 12 divided the number of months in which data are missing.

[8]F.B.I. population in Census years is very similar to the population obtained by the U.S. Census. For non-Census years F.B.I. produces its own population estimation. We do not believe that the possible measurement error in population relates in any way with our instrument. Moreover, we also present robustness using only Census population data. There are some missing values in the population data, we substitute this value by the mean value of population in the ORI. This procedure does not alter in any way our results and interpretation.

[9]FBI defines these crime as follows. *Murder and nonnegligent manslaughter*:: willful killing of one human being by another. *Robbery*: taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear. *Rape*: penetration, of the vagina or anus with any body part or object, or oral penetration by a sex organ of another person, without the consent of the victim. Attempts or assaults to commit rape included. *Aggravated assaults*: unlawful attack by one person upon another for the purpose of inflicting severe or aggravated bodily injury. Simple assaults excluded.

[10]U.S. places are settled concentrations of population that are identifiable by name. They can be legally incorporated under the laws of the state in which they are located (*Incorporated Places*) or not (*Census Designated Places, CDC*). CDC boundaries are defined by the U.S. Census in cooperation with local or tribal officials, and they usually coincide with visible features. They are generally updated prior to each decennial census.

[11]Baum-Snow (2007) also keeps MSA geography constant over time using definitions from 2000.

[12]We keep only information of ORIs inside one MSA. We drop all the ORIs belonging to multiple counties at the same time. We only keep observations of municipal jurisdiction crime.

information about the soil pH (United States Department of Agriculture). We use as pH measure the negative logarithm to the base 10 of the hydrogen ion activity in the soil using the 1:1 soil-water ratio method representative value. For every U.S. Census Place we compute the average pH level and information about earth slope, elevation and precipitation.[13] Second, national consumption of tetraethyl lead as gasoline additive comes from the Bureau of Mines Mineral Yearbooks (United States Bureau of Mines).

Data on firms decentralization comes from United States Census County Business Pattern (CBP) 1974-2013. This database reports the number of employed workforce and payroll for every industry and county. Data until 1998 reports information up to 4 digits SIC industries, and data from 1999 onwards up to 6 digits NAICS industries. We only keep 2 digits industries.[14] We identify in which county the city center of one MSA belongs and we compute the proportion of employment in every industry in the county over the total employment in the same MSA. If one MSA is composed only by one county we assign a missing value to the proportion of employment in every industry in the county over the total employment in the same MSA.

Our final database encompasses more than 9,750 observations from 1960 to 1991, and 7,038 observations from 1992 to 2014. All our main discussion will focus on the period from 1960 to 1991. This is given by the fact that lead poisoning increased until 1972, and the biggest effect on crime of lead poisoning in one year appears 19 years later, when affected children have the maximum probability to commit a crime. We devote Online Appendix E to discus what happens after 1991. In this period lead poisoning decreased in U.S. and as a result also crime rates decreased, but at the same time U.S. cities continue to maintain suburbanized (see Figure 1(a)). Summary statistics of our database from 1960 to 1991 are reported in Online Appendix A.

4 Instrumental variable

4.1 Background on lead poisoning

Lead is a heavy metal with several properties. It has high density, lasts longer and is more malleable than iron, is resistant to corrosion, and has relative abundance. Because of these characteristics lead was adopted historically for several uses: plumbing, solder, painting, bullets, and as a gasoline additive. According to Dapul and Laraque (2014) there are several ways through which children and adults can get exposed to lead. Ingestion sources are lead-based paint, contaminated water by lead

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[13]U.S.G.S. divides the U.S. in different map areas. Every map area is composed by different soils (components), and every component is composed by multiple layers (horizons). We use information only at soil level, that is when the distance from the top of the soil to the upper boundary of the soil horizon is 0. For every map unit we compute the weighted mean of pH of the components, weighting by the component percentage in the map unit. Finally, for every place we compute the weighted mean of pH of the map area, weighted by their area.

[14]We also aggregate data at bigger industries definitions: agriculture, good producing industries, service producing industries and other industries. We aggregate the industries as follows. *Good producing industries*: Mining, Construction and Manufacturing. *Service producing industries*: Transportation, Communications, Electric, Gas, And Sanitary Services, Wholesale Trade, Retail Trade, Finance, Insurance, And Real Estate, Services

pipes, lead settled in soil because of leaded gasoline, paint or other industrial sources, food cultivated in contaminated soils, or leaded objects (such as children's toys). The two main inhalation sources of lead has been leaded gasoline and occupational hazards in the construction, soldering, painting, plumbing, automotive and ammunition sectors.

Lead has been used since antiquity. Its use as pigment was documented in Ancient Greece and Roman pipes were largely built with lead. The use of lead for pipes, paint and as gasoline additive has followed different timing. Lead pipes were installed on a major scale in the U.S. since the late 1800s. The danger of lead pipes was increasingly documented in the late 1800s and early 1900s and by the 1920s many cities and towns were prohibiting or restricting their use (Rabin, 2008). Conversely, the use of lead in paint peaked in 1920s, and then its use declined significantly (Mielke, 1999). The Lead-Based Paint Poisoning Prevention Act, which restricted the lead content in paint, was signed in 1971, and finally lead was banned from paint in 1978.

Tetraethyl lead was mixed with gasoline from the 1920s, because it can improve engine compression by raising the octane level of gasoline. The consumption of leaded gasoline skyrocketed in post World War II because of the increase in the use of lead as antiknock gasoline additive and the increase in the number of cars. In 1965, it was discovered that lead had a pollution effect on the environment (Patterson, 1965), and several works followed in order to prove the link between gasoline and lead pollution. Patterson's work also began an intense debate between environmentalists and the strong industrial lead lobby. The phase-down of leaded gasoline in U.S. began in 1975 when the Environmental Protection Agency (EPA) required major gasoline retailers to sell at least one grade of unleaded gasoline that was required to protect new car models with catalytic converters (Nriagu, 1990). The lead phase-down continued during the 1980s when the EPA set new limits for the amount of lead in gasoline. Leaded gasoline was finally banned in 1996.

A large medical and biological literature has given evidence of the health effect of lead, in particular on neurobehavioural development in children (see Roper et al., 1991 and International Programme on Chemical Safety, 1995). Lead is a potent neurotoxin which alters the formation of the brain and as a result influences the formation of cognitive and non-cognitive skills (see Toscano and Guilarte, 2005 and Cecil et al., 2008). According to Roper et al., 1991, "Children are at higher risk for lead exposure because they have more hand-to-mouth activity and they absorb more lead than adults". It has been shown that even low level exposure to lead during childhood is related to cognitive and behavioral outcomes, such as lower IQ, ADHD, and hyperactivity (see Banks et al., 1996, Canfield et al., 2003, Chandramouli et al., 2009, and Nigg et al., 2010). Moreover, early age lead poisoning has been found to relate to antisocial behaviours, such as aggressivity, violence and impulsivity, increasing the risk of delinquency (see Denno, 1990, Needleman et al., 1996, and Needleman et al., 2002). Likewise, prenatal and childhood blood lead concentrations are associated with more criminal offenses (see Stretesky and Lynch, 2001 and Wright et al., 2008). All these reported effect are given by the fact that lead damages neurotransmitter function in the brain that regulate impulse control (Aizer and Currie, 2017).

The effects of lead have been object of study in several recent works in economics. Exploiting differences in road proximity and the de-leading of gasoline, Aizer and

Currie (2017) find a causal positive effect of lead on juvenile delinquency. The positive relationship between lead and criminal behaviour has been also found by Reyes (2015a), who also exploits variation coming from the phase-down of leaded gasoline. Feigenbaum and Muller (2016) show that water pipe lead exposure increased homicide rates in the 1920s and 1930s, instrumenting lead exposure by city distance from lead refineries. A second strand of works found a negative causal effect of early childhood lead exposure on academic achievement (Aizer et al., 2016, Reyes, 2015b, Grönqvist et al., 2016, and Ferrie et al., 2012). Similarly, Billings and Schnepel (2017) estimate how lead-remediation policies can reverse the negative outcomes of lead poisoning. A last group of research identifies the positive effect of lead exposure on mortality in the 1920s exploiting variation from water pipe lead poisoning coming from different water acidity, measured by the water pH (Troesken, 2008, and Clay et al., 2014).

In this paper we are interested in obtaining exogenous variation of crime rates in the U.S. in the years between the 1960s and the 1990s, a period in which the U.S. experienced a dramatic increase in violent crime. We exploit the massive increase of national consumption of leaded gasoline and its effect 19 years later on violent crime, when poisoned children had the highest potential for delinquency. The time relationship between national levels of violent crime and lagged tetraethyl lead is evident from Figure 2. In fact, the increase in tetraethyl lead matches with the posterior increase in violent crimes, the two time series reaching their peaks in 1972 and 1991, respectively. We exploit official national levels of lead poisoning by gasoline published by United States Bureau of Mines (United States Bureau of Mines) rather than local levels. The reason for this choice is that local lead exposure can be correlated with potential confounders of suburbanization, such as the proportion of highways and cars in a city.

[INSERT FIGURE 2 HERE]

We obtain geographical variation of the effect of lead on crime by exploiting the fact that lead is absorbed differently by different types of soil. Lead released from combustion of leaded gasoline becomes airborne and accumulates in the top 1 to 2 inches of soil. Evidence suggests that the bioavailability of lead in soil reaches its lowest level with a near-neutral soil pH, i.e. when the pH of the soil is around 6.5 or 7 (Reddy et al., 1995, Stehouwer and Macneal, 1999 and Peryea, 2001).[15] Despite the existing evidence on the fact that the bioavailability of lead decreases between acidic and near-neutral soils, where it reaches its minimum value, we are not aware of any study about bioavailability in very alkaline soils (pH higher than 7.5).

Children can ingest residual lead in the soil by eating the soil or inhaling it because of air dust resuspension (Laidlaw and Filippelli, 2008, Zahran et al., 2013, and

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[15]The bioavailability of lead in soil depends on its solubility, i.e. how tightly it is held by soil particles (Stehouwer and Macneal, 1999). Lead is more soluble in acidic soils (pH lower than 6.5), and it is less soluble in neutral soils (pH between 6.5 and 7.5). Lead availability is considered to be minimized when the pH of the soil is higher than 6.5 or 7. This is given by the fact that the existence of solid-phase phosphates in the soil can induces the dissolution of lead mineral and its desorption. That is, the desorption of lead causes the formation of pyromorphites and the bioavailability of lead is reduced without its removal from the soil (Traina and Laperche, 1999). Reddy et al. (1995) conclude that mobility of lead will increase in environments having low pH due to the enhanced solubility of lead under acidic conditions.

Aizer and Currie, 2017). In fact, due to resuspension of roadside soil lead can be transported longer distances inside the city and then house dust can be contaminated by the soil attached to shoes (Filippelli et al., 2005, Hunt et al., 2006, Laidlaw and Filippelli, 2008). As a result it is not needed to live right close to a soil surface to get poisoned.[16] Several studies have assessed that the lead entering homes is a combination of lead from cars with smaller amounts of lead from paints (Clark et al., 2006, and Laidlaw and Filippelli, 2008). According to these studies this is given by the fact that lead paint particles tend to be larger than the one formed by leaded gasoline and then they do not penetrate cracks in homes.

4.2 Construction of the soil quality proxy

We multiply national lagged levels of tetraethyl lead consumption with a proxy for average soil quality at the city center level to obtain exogenous variation in crime rates. We use a function of the average soil pH in the city center as proxy for lead availability. This is in the same spirit to the use of water pH as instrument for water lead pipe poisoning done by Ferrie et al. (2012), Troesken (2008), and Clay et al. (2014). From the previously reported evidence we know that the proxy for soil quality we need to exploit has to be closer to near-neutral soil pH. For every city center, we combine data for the average pH level from the United States Geological Survey with crime observations from F.B.I. With our data, we can test that the effect of lead on violent crime is weaker at levels of pH close to 7.

We test this hypothesis estimating the marginal effect of lead on violent crime rates. We regress violent crime on the interaction of lead with polynomial of pH, up to the third order, and we plot the marginal effects computed at the mean. Figure 3 reports these results. As it is possible to observe, the effect of lead on violent crime is always positive and decreasing up to a pH of 7.5. Point estimate of the marginal effect then increases in the area of alkaline soils (pH higher than 7.5), but these variations do not appear to be significant.

[INSERT FIGURE 3 HERE]

A priori we are not sure of which interval of pH is the best in expressing lead toxicity. We apply machine learning tools to choose the most adequate instrument between the set of all potential candidates, that are dummy variables taking 1 for an interval between any possible minimum and maximum level of pH. For every possible pH interval we run the first stage regression of violent crime rate per capita over city and year fixed effects and the interaction between tetraethyl lead and the pH interval considered. We select the pH interval that maximizes the F-statistics for the relevance of our instrument.

This is similar to the regression tree method for prediction (see Breiman et al., 1984 for classic reference and Athey and Imbens, 2017 for a review). Regression trees are methods in which the covariate space is sequentially partitioned into subspaces

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[16]We exploit variation coming from natural soil only. Despite important part of cities are paved, in the city centers there is still enough variation in natural soil. Large surfaces of cities are covered by parks and playgrounds. According to Harnik et al. (2015) in 2014 for high density cities in U.S. almost 12 % of their city area is parkland, and New York and San Francisco has around 20 % of their area as parks. This proportion is likely to be considerably bigger at the time of the lead poisoning happen in the 1960s.

such that the sum of squared residuals (SSR) is minimized. That is, given a variable X, regression tree methods find the value of the split c which divide the sample by $X < c$ versus $X \geq c$ and minimized the SSR. This process can be expanded to multiple covariates and splits. In our context we look for two splits of the variable pH. Moreover, instead of minimizing the SSR directly, we maximize the F-statistics. That is, we maximize the SSR difference between a model in which we predict violent crime using only city and year fixed effects (the included instrument) and a model in which we predict violent crime using the included and excluded (the interaction between national lagged tetraethyl lead and a proxy for soil quality) instruments.

The instrument we select is the interaction between national lagged values of tetraethyl lead and a dummy taking values 1 if the pH of the soil in the city center is between 6.8 and 7.7. From now on we refer to MSA in which the average pH of the city centers is between 6.8 and 7.7 as places with good soil. All the other cities are referred as places with bad soil. Using the pH interval 6.8 to 7.7 provides a F-statistics of the excluded instrument of 262.16. The estimated coefficient of the interaction between tetraethyl lead and this soil quality proxy is -0.00528 with a standard error of 0.000326. The tetraethyl lead proxy used has been divided by its maximum level. Therefore, the effect of increasing tetraethyl lead from 0 to its maximum historical value in U.S. is increasing violent crime by 52 violent crimes less per 10,000 inhabitants in places with good soils. That is, the differential effect of lead in places with good and bad soils account for one third of the overall maximum value of violent crimes in 1990.

We summarize the results of our instrument selection procedure in Figures 4. Panel 4(a) reports all the estimated coefficients of the interaction between lead and any possible pH interval, while Panel 4(b) represents the corresponding F-statistics. As it is predicted from biological theory, the absorption of lead into soil should be weaker close to soil pH neutrality. Panel 4(a) shows exactly that first stage coefficient for dummy variables including pH levels lower than 6.5 in the good soil definition tends to be positive or non significant. As the minimum value of pH is higher than 6.5, then the interaction between lead and soil quality becomes negative and significant. Moreover, the first stage coefficients are robust around our preferred pH interval.

Changing the lower or the upper bound of the pH interval does not change the effect of the interaction between lead and pH. Similarly, the F-statistics of the first stage dramatically increases when the soil quality proxy includes near to neutrality pH levels (see Panel 4(b)). Despite the pH interval we choose is the one with the highest F-statistics, changing the upper or lower pH interval bounds does not alter the relevance of our instrument. We present robustness of our estimation to the use of other pH intervals in Online Appendix D.3.

[INSERT FIGURE 4 HERE]

Given our soil quality proxy, Figure 5 shows that the F-statistics of relevance of our instrument is maximized using the 19th year lag of national levels of lead poisoning, which is consistent with the evidence reported about the age structure of crimes by the FBI.

[INSERT FIGURE 5 HERE]

We give additional evidence of the effect of lead on crime in Online Appendix B.0.1. In Online Appendix B.0.2 we provide evidence that our generated instrument is not an outlier of the distribution of possible instrument by computing standard

errors for our soil quality proxy. We perform a placebo exercise by creating random instrument and report the results in Online Appendix B.0.3.

4.3 Identifying assumption: relevance

The first assumption we need for the validity of our instrument is relevance. We obtain time-variation of crime using the national lagged level of lead used as gasoline additive 19 years before. Cross-sectional variation of crime comes from variation in city-averaged soil lead adsorption. Figure 6 reports the different time series of crime between places with good and bad soil. In the 1960s, when tetraethyl lead was beginning its increase, the level of crime rates between good and bad soils was very similar. As treatment took place, crime increased more in places with bad soil in terms of lead adsorption. In fact, peak in crime rates in places with good soil is 66 % of the peak in places with bad soil.

[INSERT FIGURE 6 HERE]

The U.S. map in Figure 7 gives a schematic representation of the exogenous variation we exploit. All of the East Coast has bad soil in terms of lead adsorption. In the rest of the US the pH seems to be more uniformly located across cities. We will exploit only variation inside census regions and districts by controlling for geographical specific time trends, so that results cannot be driven by a East versus rest-of-the-US comparison.[17]

[INSERT FIGURE 7 HERE]

Tables 1 and 2 show the relevance of our instrument reporting the coefficient of the first stage regression and the corresponding F-statistics controlling for time trends at different geographical levels. Since some of the variables in our database are measured yearly and some only in Census years, we report the first stage estimates using all the years in our sample in Table 1 and estimates using only Census years in Table 2. Our first stage coefficient is always significant. Using all the years in the sample our F-statistics range between 262 and 47, in the cases of using only city and year fixed effects or also imposing state specific time trends. Using only census years we obtain sufficient F-statistics imposing year and MSA fixed effects and Census region specific trends. Therefore, we augment the model in Equation 1 using Census division specific trends in the case of using variables measured annually. When we use variables measured only in Census years we control for Census region specific trends.

[INSERT TABLE 1 HERE]

[INSERT TABLE 2 HERE]

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[17]Census Divisions are defined by the U.S. Census as: *New England*: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont; *Middle Atlantic*: New Jersey, New York, Pennsylvania; *East North Central*: Indiana, Illinois, Michigan, Ohio, Wisconsin; *West North Central*: Iowa, Nebraska, Kansas, North Dakota, Minnesota, South Dakota, Missouri; *South Atlantic*: Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia; *East South Central*: Alabama, Kentucky, Mississippi, Tennessee; *West South Central*: Arkansas, Louisiana, Oklahoma, Texas; *Mountain*: Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming; *Pacific*: California, Oregon, Washington.
Moreover, Census regions are defined by the U.S. Census as: *West*: Pacific and Mountain; *Midwest*: West North Central and East North Central; *Northeast*: New England and Middle Atlantic; *South*: West South Central, East South Central, and South Atlantic

4.4 Identifying assumption: exogeneity

Our identification assumption is that in years in which national consumption of tetraethyl lead increased places with good and bad soils would have had similar trends in terms of suburbanization other than through differences in violent crime. This assumption is credible if soil pH is as good as randomly assigned. We present two balancing tests to support our claim. First, we demonstrate that places with good and bad soils have parallel trends in both suburbanization and violent crimes prior to the massive increase in tetraethyl lead. Second, we show that places with good and bad soil have similar pre-trends also in terms of other observable characteristics.

Table 3 reports the balancing test for the suburbanization and crime variables. We report both the difference in levels and trends between places with good and bad soils. Moreover, we do this exercise both without controlling for any geographical aggregation fixed effect ("All U.S." columns) and also controlling for Census Division fixed effects ("Inside Division" columns). The pre-trend assumption seems to be guaranteed. As soon as we control for Census Division trends, places with good and bad soil had similar trends between the 1950 and the 1960, that is before the great increase in national use of lead as gasoline additive. To further reassure of the exogeneity of our soil quality proxy we also show level differences. Places with good and bad soil tend to be similar in terms of their pre-treatment level of suburbanization, population and crime as soon as we control for Census Division dummies.

[INSERT TABLE 3 HERE]

Balancing test for other observables are also reported in Tables 3. From Table 3 we can rule out that places with good and bad soils had different trends in other geographic and social characteristics that can influence suburbanization. It seems however that places with good and bad soils have some differences in pre-treatment levels in terms of rent, income, precipitation rates, business and manufacturing employment, public transportation and education. We show in Online Appendix D.2 that our results are robust to the inclusion of these variables as controls. It is interesting to note that places with good and bad soil are similar in terms of agriculture and mining employment. Therefore, we can rule out the possibility that soil pH is affecting suburbanization by changing the relative proportion of land used for urban and agricultural use inside a city.

Table 3 shows that places with good and bad soils are very similar in terms of pre-treatment levels and trends of highway construction. Hence, our results cannot be driven by highway construction, a channel emphasized in previous literature. We show in Online Appendix D.1 that the results we found are robust even controlling for highways, and dealing for its particular endogeneity.

In order to understand what would have happened to violent crime if the lead poisoning shock did not take place, we estimate the time-varying effects of soil pH on crime. We run regressions of the effect of soil pH interacted with year dummies on violent crime, that is Equation 3.

$$VC_{m,t}^{cc} = \mu_m + \mu_t + \chi_t 1(year = t) * good\ soil_m^{cc} + \mu_g \times \mu_t + \epsilon_{m,t} \tag{3}$$

Results of this regression are reported in Figure 8. In line with the results reported in the previous Section, between 1960 and 1991 violent crime increased less in city

14

centers with good soil. As the de-leading phase started this difference shrank. In 1996 lead was completely banned, this means that by 2014 almost all adults have suffered very little lead poisoning and people younger than 18 years old were not poisoned at all. As we observe in Figure 8 there is no statistical difference between good and bad soil city centers today.

[INSERT FIGURE 8 HERE]

This is further evidence of the exogeneity assumption. In particular, cities with good and bad soil started with the same level of violent crime when there was no lead poisoning. They then ended with no differences in violent crime, when lead poisoning was no longer relevant. Therefore, this evidence supports our claim that violent crime would have always be the same in these two kinds of cities if lead poisoning would not have been there.

Figure 8 also provides evidence in favour of the exclusion restriction. If the effect of pH on crime is only passing through its interaction with lead then the results of the estimated regressions of the effect of soil quality by year should be similar to the lagged time series of lead poisoning. The time series of the reduced form coefficients of our soil quality index mimics the lagged time series of lead, strongly supporting that the effect of pH on crime is very likely to pass only through its interaction with lead.

5 Results

5.1 Baseline Results

In this Section we first provide estimates of our main equation of interest, Equation 1, that looks at the effect of violent crime in city centers on suburbanization. As shown in column (1) of Table 4 there is a negative correlation between violent crime and the share of population that lives in the city center. As discussed previously this estimate cannot be interpreted as causal, and because of this we implement our instrumental variable methodology. That is, we predict violent crime using the interaction between lagged national lead levels and a proxy for soil quality. Column (2) shows that places with good soil experienced a slower increase in violent crime and this difference is substantial. In 1991, at the peak of lead exposure for potential criminals, a MSA with bad soil had 0.91 standard deviations more violent crimes with respect to one with good soil.

[INSERT TABLE 4 HERE]

In Column (3) we estimate the causal effect of crime on the share of people that lives in the city center using our instrumental variable strategy. Estimates show that an increase in one standard deviation in violent crime decreases the share of population living in the city center by 7.2 percentage points. The upward bias of the OLS estimate is consistent with the presence of reverse causality bias from suburbanization to violent crimes. Online Appendix C discusses for which values of the estimated coefficients the OLS bias could have been induced by reverse causality.

Column (4) reports the reduced form effect of our instrument on the percentage of people living in the city center. The effect of increasing lead from no poisoning to the

maximum level increased suburbanization in places with bad soil by 6.8 percentage points with respect to places with good soil.[18]

In Column (5) we estimate our preferred specification in which we additionally control for census division times year fixed effects. In this regression we are only exploiting differences between good and bad soil city centers that are inside the same census division. Our estimates are now robust to any potential omitted variable common to MSAs in a certain census division. As shown in Column (5), previous results are robust to this specification. According to these estimates an increase in one standard deviation in violent crime decreases the share of population living in the city center by 8.4 percentage points. This implies that if in 1991 the level of crime would have been as low as in 1960 the percentage of people that lived in the city centers would have been 15 percentage points higher[19].

Column (6) shows the same results using as dependent variable the population in city centers. A one standard deviation increase in violent crime decreases the population of the city center by 26%. The overall increase in crime rates from their level in 1960 to that one in 1991 translates into a 46% decline in city center population.

We show that our results are robust to several specifications. In Section 6.1 we show that despite the fact that lead could potentially affect educational outcomes, this channel does not bias our results. Online Appendix D discusses the additional robustness we conduct. We discuss that our results are robusts to the inclusion of possible confounders, such as highways (Online Appendix D.1) and many other possible variables (Online Appendix D.2). In Online Appendix D.3 we demonstrate that our results do not depend on the particular decision of the instrument. We also show that the effect of violent crime on suburbanization does not depend on the particular geographical variation we exploit (Online Appendix D.4). Finally, in Online Appendix D.5 we demonstrate the robustness of the standard errors estimated.

We report estimates for the effect of crime on suburbanization in the de-leading phase, after 1991, in Online Appendix E. We show that when lead poisoning decreased, violent crime rates decreased faster in places with bad soil than in places with good soil. However, in the same period places with bad soil did not decrease suburbanization, providing possible evidence for the persistence of the effect of crime on suburbanization. Online Appendix F discusses how our first and second stage results can potentially vary through time. We show that the effect of resuspended lead on violent crime is constant through decades. Nevertheless, the effect of violent crime rates on suburbanization is declining through time.

The effect of violent crime on suburbanization also presents important heterogeneity with respect to several city characteristics. We present the analysis of the mechanism and channels behind the crime effect on suburbanization in Online Appendix G. We show that this effect is stronger in cities in which the suburbs have lower levels of black population with respect to the city center. Moreover, suburbanization was stronger in cities with higher levels of previous suburbanization, that were richer, with smaller geographical constraints, and where more highways were built.

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[18]This is given by the fact that the national level of lead poisoning has been normalized by its maximum value.

[19]Violent crime per capita in city centers increased by 1.79 standard deviations between 1960 and 1991.

5.2 Magnitude of the effect of violent crime on suburbanization

To get a better idea of the size of the effects estimated in Table 4 we construct two counterfactual scenarios: one in which crime remained throughout our sample at the low level of 1960 and one in which crime in city centers increases at the same rate as in the suburbs. The time series of the share of people living in the city center in the U.S. and in these counterfactuals are displayed in Figure 9.

[INSERT FIGURE 9 HERE]

As previously described there was a clear pattern of suburbanization in the period studied. The percentage of people living in the city center moved from 44% in 1960 to 33% in 1990. Our estimates instead predict that if the US had maintained the low levels of violent crime in city centers observed in 1960, we would have seen a process of urbanization of US cities. The percentage of people living in city centers would have increased, reaching 50% in 1991.

Some caveats are necessary to have in mind when interpreting this result. First of all, we do not want to claim here that if the U.S. would have banned the use of lead in gasoline since the beginning we would not have observed any growth in violent crime since the 60s. Many factors would have influenced the violent crime rate in this period and only one of them is lead exposure. Furthermore, it is important to notice that with this counterfactual experiment we are also not exploring what would have been the suburbanization trends if all the MSAs in the U.S. would have been in our control group, namely good soil. In fact, also the MSA we used as control in our estimations have suffered an increase in crime in this period. Moreover, we are not considering that the proportion of people living in city centers could have mechanically decreased because of the limitation in space in the centers to allocate the demographic increase in population in any U.S. city.

It is likely that crime rates would have still increased in U.S. if lead poisoning had not happened. One possibility might have been that crime rates in city centers would have followed the trends that the suburbs experienced.[20] Therefore, we compute a second counterfactual experiment in which crime rates in the city center would have increased at the same rate as in the suburbs. In this case our estimates predict that if the U.S. city centers increased crime as in the suburbs then the proportion of people living in the city center would have increased only marginally. As it shown in Figure 9, the percentage of people in city centers would have increased from 44 % in 1960 reaching 45% in 1991.

Cullen and Levitt (1999) estimate that an increase in 10% in crimes rates in the city center translates into a decline in city center population by 1%. Our estimated effect has a bigger magnitude. We estimate that an increase in 10% in crimes rates in the city center translates into a decline in city center population by 2.6%.[21] The difference in magnitude can be explained by the fact that Cullen and Levitt (1999) use as instrument the punitiveness of the state criminal justice system. For instance, this

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[20]We show in the Online Appendix B.1.2 that the lead poisoning shock we are exploiting did not affect in any form the suburbs.

[21]Violent crime per capita in the city center has mean and standard deviation of 0.00577 and 0.00581, respectively. Therefore, increasing violent crimes by one standard deviation corresponds to increasing violent crime by 100.6%. We computed the effect of a 10% increase in crimes rates on population dividing -0.257 by 10.06.

instrument can influence both crime rates in city centers and suburbs. Subsequently, the increase in crime rates in the suburbs can lead to an increase in the population of city centers.[22]

We can compare our findings with the results found in similar studies of other causes of suburbanization. The relative increase in crime between city centers and suburbs from 1960 to 1991 implies a 35% decrease in the population of city centers.[23] This point estimate is higher than similar coefficients found in other studies, but it include them in its confidence interval.[24] According to Boustan (2010), black migration from the South was responsible for a 17% decline in total urban population. Baum-Snow (2007) reports that the construction of the interstate highway system led to a decrease of central city population by 23%.[25] That is, for a city like Philadelphia, with 2 million people living in the city center in 1960, 4,000 more violent crimes in 30 years move away the same number of people from the center to the suburbs as if one highway passing from city center would have been built.[26]

The different suburbanization mechanisms proposed by Baum-Snow (2007) and Boustan (2010) are likely to be complementary with the increase in crime rates. In Section 5.3 we show that suburbanization caused by violent crime has been disproportionately driven by the white population. The abandonment of city centers by whites and the consequent increase in the relative proportion of black population in city centers could have in turn made more white people move to the suburbs, consistent with the story proposed by Boustan (2010). Similarly, we show in Section 7 that the increase in violent crimes stimulate the construction of highways, which can then explain part of U.S. suburbanization (Baum-Snow, 2007).

5.3   Displacement Effects

In this section of the paper we explore whether violent crime does not only change the share of people living in the city center but displaces people from one city to another. Investigating this effect is important for two main reasons: First of all, if this was the

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[22]Cullen and Levitt (1999) control in one specification for crime rates in the suburbs and they indeed find a stronger effect of crime rates in city centers on the population in city centers. However, crime rates in the suburbs can be a bad control in that specification.

[23]The 35 % refers to the difference in change population if crime would not have increased from the 1960, 46 %, and if crime would have stayed in city centers as in the suburbs, 11 %. This last number has been found multiplying 0.257 by the standard deviation increase in violent crimes from 1960 to 1991, 1.79, and then dividing it by the relative increase in the number of crime in the city centers from 1960 to 1991 with respect to the same increase in the suburbs, 4. The relative increase in crime between the centers and suburbs has a similar magnitude by computing using the predicted crime in city centers and outside from the first stage regression

[24]The point estimate of the effect of increasing violent crimes in city centers with respect to suburbs from the levels of 1960 to the level of 1991 on the logarithm of population in the city center is 0.35 with a standard error of 0.097

[25]This number has been computed multiplying the effect of building a new highway ray in the city center, -0.09, by the average number of rays built between 1950 and 1990, 2.6

[26]This number have been found dividing the effect of building a new highway ray in the city center, -0.09, by the effect of one violent crime per capita on suburbanization, -0.0843/1.79, normalized by the population of Philadelphia living in the city center in 1960. Philadelphia city center decline from 2 million people in 1960 to 1.5 in 1991. Moreover, Philadelphia city center has 330 violent crimes per 100'000 in 1960, and 1'400 in 1991.

case it would add some difficulties to the interpretation of our estimates. If this happened, it would mean that all cities would be in some way treated by the increase in lead but for different reasons. The places with bad soil would have been treated because of the increase of violent crime in the city center, while the places with good soil would have been treated by an increase of the total population driven by the migrants escaping from the violent cities. Furthermore, it is important to understand which kind of suburbanization process is caused by an increase in violent crimes. We could observe a decrease of the percentage of people living in the city center with respect to the suburbs in a context where both of them are losing population due to an increase in violent crime, and the city center is experiencing this process at a faster pace. The other option instead is that people are moving inside the MSA away from the city center.

[INSERT TABLE 5 HERE]

Estimates in Table 5 show that violent crime does not displace people from one MSA to another but redistributes population from the city center to the suburbs. An increase in violent crime in the city center is not influencing the overall population of the MSA (see Column (1)). Increasing violent crimes by 1 standard deviation decreases the population living in city centers by 26% and increases the population in the suburbs by 14% (see Columns (2) and (3)).

Violent crime in the city centers decreased population in the city centers by a similar magnitude such as the increase in population in the suburbs. In particular, the increase in violent crimes from its level of 1960 to its level in 1991 moved an average of 83,000 people from the city center to the suburbs.[27] That means that the increase in violent crimes in the city center from their level in 1960 to their maximum level in 1991 is responsible for moving almost 25.5 million people outside of city centers in the all U.S, that is almost 0.8 million people by year.[28] For a city of the size of Philadelphia each violent crime moved on average 4 people away from city centers per year.[29] On the other hand, the increase in violent crimes from its level of 1960 to its level in 1991 increased the population in the suburbs by 62,000 people.[30]

Columns (4) and (5) show whether the racial demographic composition in the city changed because of the increase in violent crime. First, Column (4) of Table 5 shows how as city centers become more violent the percentage of blacks in the MSA does not change. This is further evidence of the fact that the phenomenon that we are studying is not displacing people from one city to the other but only moving people inside the same MSA. In Column (5) we can indeed observe that there is differential racial movements towards the suburbs. A one standard deviation increase in violent crime

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[27]This number has been found multiplying 0.257 by the standard deviation increase in violent crimes from 1960 to 1991, 1.79, and then by the average population of city centers in 1960, 181,030. The point estimate is 83,282 and its estimated standard error is 23,294

[28]This number has been found multiplying 83,282 by the number of urban cities in our sample, 306

[29]This number have been found dividing the effect of one violent crime per capita on population in city centers, 83,282, normalized by the population of Philadelphia living in the city center in 1960. Philadelphia city center decline from 2 million people in 1960 to 1.5 in 1991. Moreover, Philadelphia city center has 330 violent crimes per 100'000 in 1960, and 1'400 in 1991.

[30]This number has been found multiplying 0.144 by the standard deviation increase in violent crimes from 1960 to 1991, 1.79, and then by the average population of suburbs in 1960, 240,516. The point estimate is 61,976 and its estimated standard error is 23,032

in the city center increases the share of blacks in the city center by 4.7 percentage points. This constitutes a substantial increase as in the 1960, before the suburbanization process began, 13.4% of the population of the city center was black. This estimate provides evidence of the "white flight", that is the movement of white affluent people to the suburbs. What these estimates show is that at least part of this phenomenon may be explained by the rise of violent crime in the city centers. Moreover, the change in racial composition in the city centers could in turn explain part of the subsequent suburbanization, consistent with the mechanism proved by Boustan (2010).

5.4   Effects on employment decentralization

Glaeser and Kahn (2001) show that cities in the U.S. are characterized by decentralization of employment inside the city. In this Section we want to understand whether violent crime has caused residential suburbanization only or it might also induce decentralization of employment location inside the city. In addition we want to understand if the decentralization of firms can be caused by residential suburbanization. In fact, as a response to the residential suburbanization two processes can happen. First, firms can move to city centers because of residential suburbanization if the increase in vacant housing in the city center decreases land cost and firms are able to reconvert residential areas into business areas. This process would increase further the monocentricity of a city in terms of employment location in the Central Business District (CBD). Second, firms might follow people in the suburbs in order to reduce workers' commuting costs, with the effect of creating new employment centers in the city outside the CBD. Similarly, residential suburbs can create infrastructure in the suburbs, such as highways, that firms can exploit.

As we discuss in Section 7 the decision of decentralization of firms will have important implications for aggregate city variables, such as productivity and amenities of the city. We collect data for every MSA about the distribution of employment between the county in which the city center is located and the rest of the city. From Table 6, column (1), we do not evince that overall firms decentralize as a result of higher violent crimes. However, this result can mask sector heterogeneity in the response to the increase in violent crimes.

Manufacturing is one of the sectors that relocates the most to suburbs after the increase in crime rates in city centers. This is likely because manufacturing relies on the use of large land space which is available in the suburbs. We also find that firms in wholesale trade, retail trade and other services move to the suburbs. Finance, Insurance, and Real Estate is the most important sector which does not decentralize as a result of the crime increase. The reason for which Finance might stay in the center can be related to the fact that knowledge spillovers and spatial proximity to other firms is more important in this sector. In addition, this sector tends to locate more in skyscrapers present in the CBD. Therefore, as a result of the crime and suburbanization shock many firms are relocating in the suburbs but firms in the Finance sector, which continue to stay in the CBD, leading to the possible creation of multiple employment centers in the city with different specializations.

[INSERT TABLE 6 HERE]

We have seen that both people and firms in some sectors move to the suburbs af-

ter crime increased in the city centers. We can provide evidence of whether people has followed jobs or the opposite is true. In order to do this we have estimated the effect of violent crime on suburbanization controlling for past levels of employment decentralization and the effect of violent crime on employment decentralization controlling for past levels of suburbanization.[31] Results are reported in Table 7. As shown in Columns (1) and (3) violent crimes caused both residential and employment decentralization in the manufacturing sector. If violent crimes cause people to move to the suburbs and then firms follow people, then when we control for the past level of suburbanization we should not find any effect of violent crime on firm decentralization. This is confirmed in Column (2). In fact, it seems that jobs followed people which have escaped city centers because of violent crimes. However, the effect of crimes on suburbanization is maintained even controlling for past level of employment decentralization in the manufacturing sector (see Column (4)). That is, results suggest that the first effect of violent crime is to make people leaving city centers and, then, firms decide to follow people to the suburbs.

[INSERT TABLE 7 HERE]

6 Threats to identification and further robustness

The exclusion restriction requires that the effect of the instrument on suburbanization is only passing through its effect on crime. In terms of our setting, this means that the interaction between lagged national lead and soil quality is only affecting crime and not any other variable that can influence suburbanization. One strength of our instrument is the use of lagged values of lead poisoning that are a priori only related to crime rates. We use a lag of 19 years because this is the age in which a person has the highest probability of getting arrested for a violent crime in 1965 (see United States Department of Justice, 1993). Unless lead poisoning through soil is affecting an omitted variable with exactly the same lag of 19 years, our estimates will be consistent.

In order to fully exploit timing idiosyncrasies of crime we conduct a robustness test in which we do not only use the maximum propensity of committing crime but all the age structure of crime rate. We discuss in Online Appendix D.3 how we perform this exercise and we show that all our results are robust to this specification.

Despite people can potentially leave the city center at the time they get poisoned by lead, for example because of higher pollution, this mechanism would not invalidate our estimates. This is given by the fact that we exploit the effect that lead has on crime 19 years later and not in the same year of the poisoning. Moreover, we provide evidence that people did not leave city centers immediately. This is confirmed by the fact that places with good and bad soil do not have different pre-trends differences in suburbanization between the 1950 and 1960, as it is shown in Section 4.4. The lead poisoning shock began around the 1940s and its effect via pollution should have been manifested before the 1960s. It was only from the 1970s that public opinion became

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[31]Estimations have been conducted in the sample of years from 1974 to 1991 and without using Census region time trends in order to guarantee a sufficiently big F-statistics. In order to control for the possible endogeneity of the 10th lag of suburbanization or firm decentralization we include the interaction between the 29th lag of national lead poisoning and our soil quality proxy.

aware of the possible effect of lead poisoning by gasoline additives and the role of soil quality has not been known until relatively recently (see Reddy et al., 1995).

In Section 6.1 we discard the possibility that lead poisoning can affect suburbanization via its effect on cognitive abilities. We present additional evidence in favour of the exclusion restriction in Online Appendix B. We use the control function approach to give evidence that the effect of lagged lead 19 years before is likely to pass only via crime (Online Appendix B.1). We demonstrate that the particular function of pH we use for our instrument is unlikely to be related to agricultural productivity of one city (Online Appendix B.1.1). We show that there is no spillover from the city centers to the suburbs of crime rates and that the only variation in crimes caused by lead happen in city centers (Online Appendix B.1.2). In fact, it might be possible that crime in the suburbs increased because people poisoned by lead in the city center either relocate to the suburbs or displace to commit crimes to the suburbs. However, we do not find evidence supporting this claim. We find non-statistically significant coefficients of both good soils in the suburbs and in the city center on crime rates in the suburbs. We provide evidence that lead poisoning is only affecting violent crimes and not other crimes, as it is predicted by medical literature (Online Appendix B.1.3).

6.1 Potential confounders: cognitive abilities

Recent works have shown that lead poisoning has an effect on child educational attainment (see Aizer et al., 2016, Reyes, 2015b, Grönqvist et al., 2016, and Ferrie et al., 2012)). Education levels and human capital can bias our results if the effect of education on suburbanization follows the same age-structure as crime. If parents decide to suburbanize because of lower cognitive abilities of student peers of their children, this would not be a problem for our estimates since this effect should manifest before the 19-year lag when children are in school age.

Our estimates would be biased if people decide to suburbanize because of their own lower human capital skills. For example, lead poisoning could make people more anxious or racist and then decide to leave city centers. If this channel takes effectively place we should see that people with lower human capital are the one suburbanizing the most. Table 8 reports evidence against this possibility, by showing the demographic profile of people suburbanizing between 1975 and 1980.[32] People that decide to suburbanize have on average 31 years, they are more likely to be white, they tend to have higher high school performances, even between the category of whites, and they tend to have better occupational outcomes.

[INSERT TABLE 8 HERE]

Therefore, it is unlikely that people suburbanize because they get directly lead poisoned. Whites are more likely to suburbanize, and there is evidence of racial disparities in lead poisoning. In fact, Sampson and Winter (2016) demonstrate that black neighborhoods exhibited extraordinarily high rates of lead toxicity compared to white neighborhoods. Table 9 shows that the higher propensity of violent crime of the black population is exacerbated by the presence of highways passing through the city cen-

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[32]The U.S. Census conducted in 1980 allows us to construct the demographic profile of people who left city centers for suburbs in the last 5 years. We could not construct the same statistics for different Census years.

ter in years in which lead poisoning was higher. This is because the black population tends to live closer to highways and then they are more likely to get poisoned by lead. Similarly, we show in Online Appendix G that the effect of resuspended lead on crime is stronger in cities in which the city centers has more highways and a higher proportion of blacks.

[INSERT TABLE 9 HERE]

Additionally, our estimates would be biased if people decide to suburbanize because of lower human capital skills of other people in city center caused by lead poisoning. For this channel to be a problem, lead should affect human capital skills with the same age-structure as the one used to predict crime. In Table 10 we regress a proxy for human capital skills, the percentage of people with high school diploma, on the interaction between our soil quality index and different lead lags.[33] Column (1) shows that lead can influence human capital but in a different way from which it affects crime. We only find the 29th lag of lead significant to predict education outcomes. In contrast, the 19th lag is not significant. One possible explanation for this result is that lead affects violent crime which then influences the return of education, leading to a decrease of education 10 years later. However, the result that on aggregate lead can influence educational outcomes is not consistent with the use of different clustering in the standard errors, which takes into account the possible geographical correlation at Census district level in the errors. In fact, from Column (3) we cannot confirm the effect of the 29th lag of lead poisoning on the share of high school graduates in a MSA.

[INSERT TABLE 10 HERE]

We demonstrate in Table 11 that our estimates of the effect of crime on suburbanization are robust to the inclusion of the interaction of soil quality and lead poisoning 29 years before, which can indirectly influence educational outcomes. Column (1) reports the negative effect of violent crime on suburbanization using Census region times year fixed effects.[34] In column (2) we augment our estimations by also controlling for the 29th year lag of lead poisoning. We obtain similar results as when we do not control for other lags of lead poisoning.

[INSERT TABLE 11 HERE]

If the effect of lead is affecting suburbanization because it decreases human capital in the city and not because it influences crime we should expect a positive IV estimate of the effect of a proxy of human capital on the proportion of people living in city centers. Table 11 column (3) contradicts this hypothesis. While in Column (1) we observe that the IV estimate of violent crime on the share of population in the city center is negative, the effect of the share of high school in one MSA is also negative using resuspended lead as instrument. That is, it is possible that the estimation in Column (3) is biased because crime and education are correlated and resuspended lead is affecting crime alone.

To further discard the possibility that suburbanization might happen because of lower human capital in the city center, we run our estimation of the effect of crime controlling for instrumented values of educational attainment in the city. We in-

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[33]We use the percentage of people in the MSA with high school diploma from Baum-Snow (2007) as proxy for educational attainment. Since we have data about percentage of people with high school diploma for decennial years we use the 9th, 19th and 29th lag of lead poisoning.

[34]We use these fixed effects because education is measured every Census year.

strument educational attainment using historic state compulsory education laws collected by Goldin and Katz (2008). In particular, we use two different measures of minimum age of compulsory schooling in 1910 as instruments: the school entrance age and the school leaving age. We obtain a time variant instrument for education by multiplying minimum age of compulsory schooling by the U.S. proportion of people with high school in a particular year. Results are reported in Table 12.

[INSERT TABLE 12 HERE]

Columns (1) and (2) replicate our unconditional results. Columns (3) and (6) jointly estimate the effect of violent crime and education on suburbanization using the two different education instruments (columns (4)-(5) and (7)-(8) show the corresponding first stage regressions). Both column (3) and (6) show that the effect of crime on suburbanization is robust to the inclusion of an instrumented education control.

7   Effect of crime on aggregate city variables

We have shown that violent crime has moved people and firms from city centers to the suburbs. In this Section we explore whether this increase in violent crime and suburbanization has generated any aggregate effects on the city or if suburbanization is just a zero sum reshuffling of resources around the city. This is an important question to tackle in order to gain understanding on how people and firms should be distributed in a city.

We first explore this question by looking at the effect that violent crime had on the total population of the city, house prices and median income. Results in Table 13 show that violent crime had no effect on city population while median income and house prices in the city increased. In fact, from Section 5.3 we already know that violent crime has only created movement of people inside the city and not between cities. From Column (2) and (3) we can see that violent crime has a positive effect on MSA housing affordability both measured as median gross rent per housing unit (Column (2)) or median single family house value (Column (3)). Moreover, we find that the increase in violent crimes is associated with higher income also controlling for the education levels (Columns (4) and (5)).

[INSERT TABLE 13 HERE]

In Table 14 we explore further what are the income effects of violent crime and if violent crime generated any changes in the means of transportation used in a city. We observe, first of all, that while income increased overall in the city these gains have not enjoyed by people living in the city center. In fact, we observe that overall inequalities increase in the city. In Column (1) we can observe that the Gini index within the city increased.

[INSERT TABLE 14 HERE]

In Column (2) of Table 14 we can observe that the ratio between income in the city center and the MSA decreased. In the city center the median income has decreased but not in a statistical significant way (Column (3)). On the other hand, the overall income in the MSA has increased indicating that suburbs have become particularly richer. This results are interesting because they uncover two dynamics that happen as a city becomes more violent and therefore suburbanized. The first is a selection process, where richer individuals move to the suburbs leaving the poorest in the city

center. This is also in line with the results shown in Tables 5 and 8 on how the racial distribution of people inside a city changes after an increase in violent crime.

The second can be understood in combination with the fact that the cities that are becoming more violent and more suburbanized are not losing population. A way to make this possible is that incomes in the MSA increase to compensate for the increase in violent crime, the increase in transportation cost, and other negative amenities that the suburbanization process may generate. These two effects combined create the observed changes in income after an increase in violent crime. In the city center, the two effects might go in opposite directions. Because of selection only the poorest people stay but they have to be compensated with an increase in income so that they do not migrate to another city. The overall effect is that their income remains unchanged. Instead in the suburbs the two effects might reinforce each other. The increase in violent crime moves the richest people to the suburbs and added to this they also need to be compensated for all the negative amenities.

It is important to notice that these results do not fit with a model in which violent crime is only decreasing the amenities of a city. In that case, one would expect violent crime to decrease the population and/or to decrease house prices. Another mechanism that can explain these results is that the increase in violent crime has generated some positive externality on productivity. In fact, we know from Table 6 that violent crime increased employment decentralization, and city with multiple employment centers can be more productive.

Finally, we explore if violent crime generated also changes in the way that individuals move around the city. From Column (4) of Table 14 we can see that violent crime boosts the construction of highways possibly to facilitate suburbanization of people. The construction of new infrastructure can potentially have effects on productivity of the city. Moreover, since we know from Baum-Snow (2007) that highways have a positive effect on suburbanization, the effect of violent crime on suburbanization that we have found in Section 5.1 has to be interpreted as the general equilibrium effect of violent crime on suburbanization which do not partial out for the mediating factor of the highway construction. In column (5) we further observe that violent crime decreases the use of public transportation. These two last results confirm the fact that violent crime generated suburbanization and this ultimately decreased the demand for the use of public transportation and increased the demand for highways and the use of car.

From the results of this Section we can speculate that amenities and productivity in the city might have been affected by the increase in violent crimes. In the next Section we build a spatial equilibrium model in which every city is considered as a different economy in order to make sense of these between-cities comparisons and assess whether violent crime has influenced amenities and productivity.

7.1   Spatial equilibrium model

We rationalize the city-wide effects of violent crime using the Rosen-Roback spatial equilibrium model developed by Glaeser (2008) and Glaeser and Gottlieb (2009). The model has its base in the works of Rosen (1979) and Roback (1982), and the cornerstone of the model is the concept of spatial equilibrium: utility should be equalized

between people living in different spaces. The same model has been applied to study the aggregate effect of city shape by Harari (2015). Each city (m) differs for its specific level of amenities (θ_m) and productivity (A_m). We assume that violent crime has an effect on these parameters. Our goal is to estimate how large and in which direction the effect of violent crime on these parameters has to be to match the city-wide estimates. The model consists of three agents: workers, firms in production sector and firms in construction sector.

Workers (i) have to decide in which city m to live. We assume perfect mobility between cities. Moreover, they have to decide how much to consume of a consumption good (C) and housing (H). The price of the consumption good is normalized to 1, while the price of housing is specified as p_m^H. They supply inelastically labour and obtain a city-specific wage (w_m). We assume a Cobb-Douglas utility function, where α represents the share of housing into utility. If a city has a higher level of amenities (θ_m) workers receive higher utility from that. The problem of workers is therefore the following one:

$$\max_{C_i, H_i} \quad \theta_m C_i^{1-\alpha} H_i^\alpha$$
$$\text{s.t.} \quad C_i = w_m - p_m^H H_i$$

The solution of the worker's problem gives rise to the so-called spatial equilibrium condition. Let's define $\bar{v}_m$ as the indirect utility that should be equalized between cities. Plugging the optimal solution for the amount of housing, $H_i = \frac{\alpha w_m}{p_m^H}$, and consumption good, $C_i = (1-\alpha) w_m$, into the utility and taking logs we can write the spatial equilibrium condition as in Equation 4. Lower amenities in one city should be compensated by higher wages or lower house prices to obtain the same utility between cities.

$$log\left(\bar{v}_m\right) = (1-\alpha)\,log\left(1-\alpha\right) + \alpha\,log\left(\alpha\right) + log\left(\theta_m\right) + log\left(w_m\right) - \alpha\,log\left(p_m^H\right) \quad (4)$$

The representative firm in production sector decides the amount of labour (N) and traded capital (K) to hire to produce the consumption good. Labour is paid the wage level (w_m). Traded capital can be purchased at a price of 1 in any location. Every city is characterized by a specific level of productivity (A_m) and a fixed-supply of non-traded capital ($\bar{Z}_m$). As reported in Glaeser (2008), the assumption of the existence of traded and non-traded capital allows to have firms facing constant returns to scale but to have decreasing returns to scale at city level, and then the presence of a finite number of firms in each city. We assume a Cobb-Douglas production function where β and γ represent the share of labour and traded capital into the production function. The problem of the firms in the production sector follows.

$$\max_{N, K} \quad A_m N^\beta K^\gamma \bar{Z}_m^{1-\beta-\gamma} - w_m N - K$$

The solution of this problem gives rise to the labour demand condition reported in logarithm terms in Equation 5.

$$log\left(w_m\right) = log\left(\beta\right) + \frac{\gamma}{1-\gamma}\,log\left(\gamma\right) + \frac{1}{1-\gamma}\,log\left(A_m\right) + \frac{1-\beta-\gamma}{1-\gamma}\left[log\left(\bar{Z}_m\right) - log\left(\bar{N}\right)\right] \quad (5)$$

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The last actor of our model are the firms in the construction sector. The representative firm decides how many houses to build (H) in each city and sell them at p_m^H. For each house the construction firm decides the combination of height (h) and lot size (L) of the house to build, such that $H = h \times L$. The quantity of land used should not exceed the potential spread of the city given by geographical or political constraints ($\bar{L}_m$). The cost of the land is p_m^L. In addition to the land cost, the cost of building, $C(H)$, depends on the height of the housing unit to build. The cost of building high is assumed to be convex: adding one more floor to a house lead to a more than proportional increase in construction costs. This assumption is parametrized imposing $\delta \geq 1$.[35] While δ refers to the current technology to build higher, which is common across cities, c_m refers to a city-specific factor that influence the cost of height. The problem of the firms in the construction sector follows.

$$\max_{H,L} \quad p_m^H H - C(H)$$

$$\text{s.t.} \quad H = h \times L; \qquad\qquad L \leq \bar{L}_m$$

$$C(H) = c_m h^\delta L + p_m^L L; \qquad \delta > 1$$

The solution of this problem gives rise to the height demand condition reported in logarithm terms in Equation 6.

$$log(h) = \frac{1}{1-\delta}\left[log(c_m) + log(\delta)\right] + \frac{1}{\delta-1}log\left(p_m^H\right) \qquad (6)$$

Markets should clear in equilibrium. The amount of labour hired by the firms in production sector should be equal to the total population of the city (N_m). The demand for consumption good equals its supply. Moreover, the housing market equilibrium requires that the total supply of houses, $h\bar{L}_m$, equalizes its demand, HN. From the housing market equilibrium we can obtain the price equation reported in logs in Equation 7.

$$log\left(p_m^H\right) = \frac{1}{\delta}\left[log(c_m) + log(\delta)\right] + \frac{\delta-1}{\delta}\left[log(\alpha) + log(w_m) + log(N_m) - log\left(\bar{L}_m\right)\right]$$
$$(7)$$

Using the spatial indifference (Equation 4), labour demand (Equation 5), and house price equations (Equation 7) it is possible to derive three structural equations, denoted with *, that model the behaviour of house prices, wages and city population in function of city-specific parameters: productivity (A_m) and amenities (θ_m). Let's define K_m^P, K_m^w, and K_m^N as constant terms that influences house prices, wages and population respectively without passing through productivity and amenities. These constant terms also include the effect of non-traded capital, the indirect utility value and the potential land spread of the city given by geographical constraints.[36] The three structural equations are reported in Equations 8 to 10.

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[35]Evidence for this assumption has been obtained by Ahlfeldt and McMillen (2015). In fact, they conclude that a reasonable value for δ is 2.7, which is the inverse of elasticity of building height with respect to land prices.

[36]We can derive the theoretical predictions of the effect of $\bar{L}$. More potential land of the cities decreases house prices by increasing housing supply available in the city. Bigger land in the city increases population and then it decreases wages.

$$log\left(p_m^{H*}\right) = K_m^P + \frac{(\delta - 1)\left[log\left(A_m\right) + \beta log\left(\theta_m\right)\right]}{\delta\left(1 - \beta - \gamma\right) + \alpha\beta\left(\delta - 1\right)} \tag{8}$$

$$log\left(w_m^*\right) = K_m^w + \frac{\alpha\left(\delta - 1\right)log\left(A_m\right) - \delta\left(1 - \beta - \gamma\right)log\left(\theta_m\right)}{\delta\left(1 - \beta - \gamma\right) + \alpha\beta\left(\delta - 1\right)} \tag{9}$$

$$log\left(N_m^*\right) = K_m^N + \frac{\left[\delta - \alpha\left(\delta - 1\right)\right]log\left(A_m\right) + \delta\left(1 - \gamma\right)log\left(\theta_m\right)}{\delta\left(1 - \beta - \gamma\right) + \alpha\beta\left(\delta - 1\right)} \tag{10}$$

The theoretical predictions of our model are that house prices increases if a city becomes more productive or increases its amenities. Wages are positively affected by productivity. A decrease in amenities in the city should be compensated by higher wages in order to equalize utility at each location, ceteris paribus. Finally, city population increases city productivity and amenities.

We assume that violent crime (VC_m^{cc}) can have externality effects on city productivity and amenities that are not taken into account by actors.[37] We assume that the exogenous part of violent crime ($\widehat{VC}_m^{cc}$) has a log-linear influence on these parameters. We define λ^A and λ^θ as the reduced form elasticities of productivity and amenities with respect to violent crime, respectively. We assume that city productivity and amenities are further influenced by constant terms (K_m^A and K_m^θ) and any other non-constant factor not related to violent crime which composes errors (μ_m^A and μ_m^θ).

$$log\left(A_m\right) = K_m^A + \lambda^A log\left(\widehat{VC}_m^{cc}\right) + \mu_m^A \tag{11}$$

$$log\left(\theta_m\right) = K_m^\theta + \lambda^\theta log\left(\widehat{VC}_m^{cc}\right) + \mu_m^\theta \tag{12}$$

We are agnostic about the direction of the effects of violent crime on city-specific parameters. Violent crime can in principle decrease city amenities because people are not willing to live in a city with more crimes. Violent crimes can decrease productivity by influencing human capital accumulation of the population.

Our objective is then to obtain the direction of the effects of violent crime on city-specific parameters that are in line with the estimated regressions of the city-wide effects of violent crime on house prices, wages and city population using the strategy proposed by Glaeser (2008). In order to do this we substitute Equations 11 to 12 into the structural equations (Equations 8 to 10) to obtain the reduced form equations that links violent crime to house prices, wages and city population (Equations 13 to 15). As it is possible to see these equations do not depend anymore on productivity and amenities.

$$log\left(p_m^{*H}\right) = K_m^P + B^P log\left(\widehat{VC}_m^{cc}\right) + \mu_m^P \tag{13}$$

$$log\left(w_m^*\right) = K_m^w + B^w log\left(\widehat{VC}_m^{cc}\right) + \mu_m^w \tag{14}$$

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[37]The model can be expanded to include the effect of violent crime on total land spread because for example it can influences zoning and regulation constraints. However, no result that we derive depends on the assumption of no effect of violent crime on total land spread. This is similar to what has been done in Harari (2015)

$$log\left(N_m^*\right) = K_m^N + B^N log\left(\widehat{VC}_m^{cc}\right) + \mu_m^N \tag{15}$$

The reduced form elasticities of house prices, wages and city population with respect to violent crime (the B coefficients) are reported in Equations 16 to 18. These reduced forms coefficients depend on a set of parameters and on the reduced form elasticities of productivity and amenities with respect to violent crime (the λ parameters). In particular, we have a set of three equations (B^P, B^w and B^N) and two unknowns (λ^A and λ^θ). If we know the reduced form elasticities of house prices, wages and city population with respect to violent crime we can potentially recover the reduced form elasticities of productivity and amenities with respect to violent crime.

$$B^P = \frac{(\delta - 1)\lambda^A + \beta(\delta - 1)\lambda^\theta}{\alpha\beta(\delta - 1) + \delta\left(1 - \beta - \gamma\right)} \tag{16}$$

$$B^w = \frac{(\delta - 1)\alpha\lambda^A - \delta\left(1 - \beta - \gamma\right)\lambda^\theta}{\alpha\beta(\delta - 1) + \delta\left(1 - \beta - \gamma\right)} \tag{17}$$

$$B^N = \frac{[\delta(1 - \alpha) + \alpha]\lambda^A + \delta\left(1 - \gamma\right)\lambda^\theta}{\alpha\beta(\delta - 1) + \delta\left(1 - \beta - \gamma\right)} \tag{18}$$

The strategy proposed by Glaeser (2008) requires to first regress house prices, wages and population of MSA on violent crime. In this way it is possible to estimate $\hat{B}^P$, $\hat{B}^w$, and $\hat{B}^N$, the reduced form elasticities of house prices, wages and city population with respect to violent crime. In order to obtain the effect of the exogenous part of violent crime on prices, wages and population we estimate Equations 13 to 15 using our instrumental variable strategy. Moreover, we proxy the constant terms (K_m^P, K_m^w, and K_m^N) by MSA and year fixed effects. The fixed spread of cities is captured by the MSA fixed effects. Moreover, we have demonstrated in Section 4.4 that our instrument is not related to the area of a city. Fixed effects at city level also captures non-traded capital. We also include Census Region time trends in our specification.[38]

Once we estimate $\hat{B}^P$, $\hat{B}^w$, and $\hat{B}^N$ we can recover the effect of violent crime on productivity and amenities (λ_A and λ_θ) that rationalizes its city-wide effects using Equations 19 and 20.

$$\lambda^A = \left(1 - \beta - \gamma\right)\hat{B}^N + \left(1 - \gamma\right)\hat{B}^w \tag{19}$$

$$\lambda^\theta = \alpha\hat{B}^P - \hat{B}^w \tag{20}$$

In our model we assume that agents are not heterogeneous. There exists an important literature explaining why people sort in different locations based on on their productivity and valuation of amenities (see Combes et al., 2008). We do not suspect that this important mechanism can bias our estimations since we have previously demonstrated that the change in violent crime did not alter the distribution of people between cities. Therefore, the estimated effects of violent crime on productivity and amenities can be interpreted as the effect which is not caused by sorting.

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[38]Because we compare cities inside the same Census regions our assumption of perfect mobility of people is more likely to be satisfied.

We assume some parameters in order to obtain the effect of violent crime on productivity and amenities. We approximate the share of housing in utility (α) by the total consumption expenditure to housing to be 0.3, obtained from the U.S. B.L.S. Consumption Expenditure Survey. As for Glaeser (2008), we assume the share of labour and traded capital in production function (β and γ) to be 0.6 and 0.3, respectively.

7.2   Estimating the externality effects

The strategy described in the previous section allows us to map reduced form elasticities of the effect of violent crime on observable variables, such as house prices, income and population in the MSA, on reduced form elasticities of the effect of violent crime on unobservable variables, such as productivity and amenities. That is, we can understand how violent crime might have changed these unobservable variables in a way that is consistent with the model reported in the previous section.

The effect of violent crime on the observable variables is reported in Table 15. These results are slightly different from the results obtained in Section 7 because we need to use a log-log specification in order to link these reduced forms to considerations about the externality effects of violent crime on productivity and amenities. However, we can still conclude that violent crime has a positive effect on city income, and house prices, leaving population unchanged.

[INSERT TABLE 15 HERE]

Using Equations 19 to 20, we can recover how productivity and amenities should have changed in order to rationalize the effect of violent crime on house prices, income and population in the MSA. The calculated externality effects of violent crime on productivity and amenities (λ^A and λ^θ) are reported in Table 16, column (2).[39] We find a negative and significant effect of violent crime on amenities (λ^θ) and a positive effect on productivity (λ^A), with an elasticity of -0.0991 and 0.1243 respectively. Using the theoretical predictions of our model if violent crime might affect amenities as a result income should have increased as we found in Table 15. However, if amenities would have been the only city-specific factor changing this should have been reflected in lower house prices, an effect that we do not observe. Therefore, productivity should have necessarily increased as a result of higher violent crimes.

[INSERT TABLE 16 HERE]

The estimates in Table 20 imply that the increase in violent crime in the city center between 1960 and 1991 led to a decrease in the average amenities of the city of 23.2%.[40] Using equation 4 we can see that this quantity corresponds to the percentage of the wage people would have been willing to sacrifice in 1991 to return to violent crime rates in the city center as in 1960.

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[39]Standard errors of the coefficients have been obtained using the following bootstrap technique. This strategy consists in first bootstrapping a panel sample from our distribution of observations; subsequently, we have estimated the elasticity of house prices, income and population to violent crime and then compute the corresponding elasticity of amenities and productivity to violent crime; we have replicated this procedure several times and obtained a distribution of these parameters and relevant standard errors.

[40]Log violent crime in 1960 and 1991 was -7.08 and -4.73, respectively. We have computed the change in average amenities between 1960 and 1991 multiplying the elasticity of amenities to violent crime, -0.099, to the change in log violent crime in that period, 2.34.

We now explore if these effects are due directly because of the effect of violent crime or by the effect of other variables that were affected by violent crime and ultimately influenced productivity and amenities. In order to separate the real direct effect of violent crime on city-specific factors we control for several possible mediating factors that we have found to be influenced by violent crime: highways, residential suburbanization and employment centralization. The results are reported in Table 16, columns (3) to (5), respectively. By controlling for these variables, we can partial out the externality effect of violent crime which is not passing through these channels.

From Column (3) of Table 16 we can infer that, despite cities with more violent crime lead to the creation of more highways, this last effect cannot explain why cities have higher levels of productivity. The effect of violent crime on productivity which is not passing through residential suburbanization is still positive, as it has been shown in Column (4) of Table 16. Moreover, controlling for the effect of violent crime on residential suburbanization we find a negative and stronger effect of violent crime on city-amenities, with a calculated elasticity (λ^θ) of -0.1068. That is, if city centers increase their violent crimes and people cannot suburbanize then the impact of violent crime on amenities is negative.

Finally, when we control for employment decentralization we do not find any externality effect of violent crime on unobservable variables (see Column (5) of Table 16). The elasticity of violent crime on productivity (λ^A) is now not significant and equal to 0.1887. That is, the previous positive effect of violent crime on productivity could be explained by the fact that violent crime led to a creation of different employment centers in the city and this could boost firm productivity. This might mean that some firms were inefficiently located in the city center. Violent crime displaced firms in the suburbs, and this displacement was productivity-enhancing. One possible explanation for this result is that historically it might have been more efficient to have firms in the city center. Modern cities might have a different optimal distribution of firms in the city, for example as predicted by Lucas and Rossi-Hansberg (2002).[41] For an individual firm it might not be optimal to move outside the city center, despite the fact that productivity could increase if all firms coordinated this move outside of the city center. Crime could have acted as a tax to firm location in city center that solved this coordination failure by making people and firms move.

The coefficient of the effect of violent crime on amenities also turns to be insignificant. The calculated elasticity of violent crime on amenities (λ^θ) is now -0.164. This might be explained by the fact that part of the decrease in amenities in the city is explained by the fact that violent crime lead to employment to be located further away from the center. As a result amenities could potentially decrease because of higher traffic and congestion externalities.

8   Concluding remarks

In this paper we provide evidence of a debated mechanism that can explain why U.S. cities suburbanized between the 1960s and the 1990s: the increase in violent crime in

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[41]Lucas and Rossi-Hansberg (2002) predict that cities in equilibrium should have a business center in the CBD, and further away: residential, business, mixed use, business, and residential areas respectively

city centers. We estimate the causal effect of crime on suburbanization exploiting a new instrument which combines time variation from national level of past lead poisoning and geographical variation from local soil quality. We find that an increase in one standard deviation in violent crime decreased the share of population living in the city center by 8 percentage points. We provide counterfactual evidence that if violent crime in city centers would have increased at the same rate as the suburbs then the proportion of people living in city centers in the U.S. would have been constant between 1960 and 1990.

The advantage of our empirical methodology is to be able to compare all the cities in the U.S. for many decades by exploiting a standardized measure, such as the pH of the soil of a city. The use of lead poisoning as time variation of our instrument has the convenience that it can be employed to predict both the big rise of American crimes between the 1960s and the 1990s and the fall afterwards. More micro-evidence should be provided to show the link between resuspended lead and blood lead levels. This can contribute to the discussion about how much of the crime variation in the U.S. can be explained by lead poisoning.

Further research should be dedicated to the study of the big fall of crimes after the 1990s. In particular, it is crucial to understand why suburbanization did not revert when crimes decreased and what are the mechanisms behind the persistence in suburbanization. One possibility is that the flight from city centers affected amenities in the suburbs by increasing school and housing quality.

Additionally, the interaction between lead poisoning and soil quality can potentially provide quasi-experimental variation that can be used to understand the effect of crime on many other outcomes. Furthermore, our methodology could be also easily applicable to other countries. Expanding the context of analysis to European countries it might possible to understand the importance of several other urban amenities and characteristics to explain suburbanization.

The results we find are important in order to understand how much urban amenities and productivity can explain location of people and firms inside cities. Using a spatial equilibrium model we infer that the increase of violent crimes created important spillover effects at city level by reducing the overall level of city amenities. Inequalities in cities with higher crimes also increased and racial location segregation happened because of white people moving to the suburbs. The model we exploit in this paper can potentially be expanded in the future in order to assess how amenities react differently between suburbs and city centers after violent crimes increased. Another possible extension of the model is to make the land spread of the city endogenous to disentangle the different theoretical effects of crime and suburbanization.

We provide suggestive evidence that the job decentralization caused by higher violent crimes in the city center is the responsible for increasing city productivity. This is consistent with a situation where it is optimal for firms to move to the suburbs but they do not because of coordination failures. Violent crime potentially provide a common shock that solves this sub-optimality. This result points to the fact that cities could achieve gains in productivity by using incentives to move firms to the suburbs. Further research should be devoted in incorporating this coordination failure in our model and show the gains of different employment centers inside cities.

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9 Figures and Tables

9.1 Figures
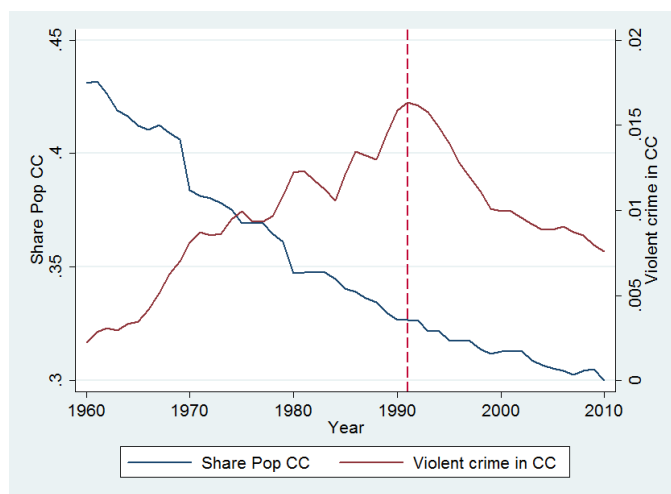
(a) Time series
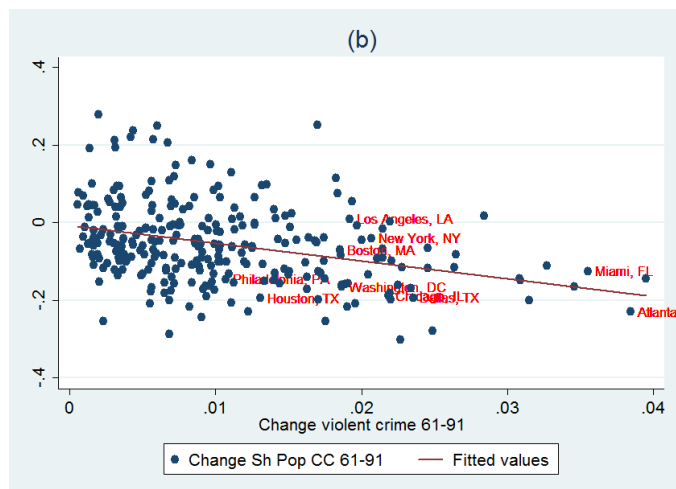
(b) Scatter plot

Figure 1: Correlation between violent crime per capita and proportion of people living in the city center

Panel a): Time series share population living in city center (CC), left y axis, and violent crime per capita in city center, right y axis. Panel b): Scatter plot change share population living in city center (CC) between 1961 and 1991 against change violent crime per capita in city center.
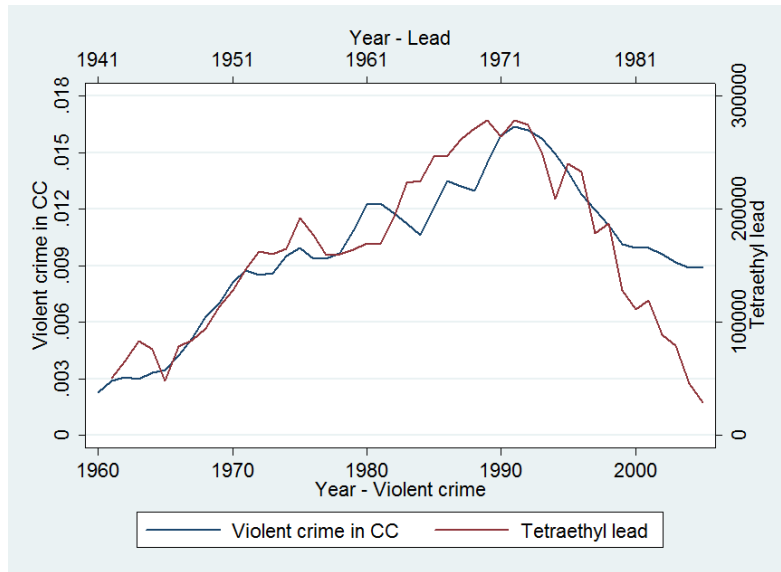
Figure 2: Time series of violent crime rates per capita and the consumption of tetraethyl lead 19 years before

Upward x axis: time series of tonnes of lead consumed in U.S. as gasoline additive. Downward x axis: time series of violent crime per capita in city center
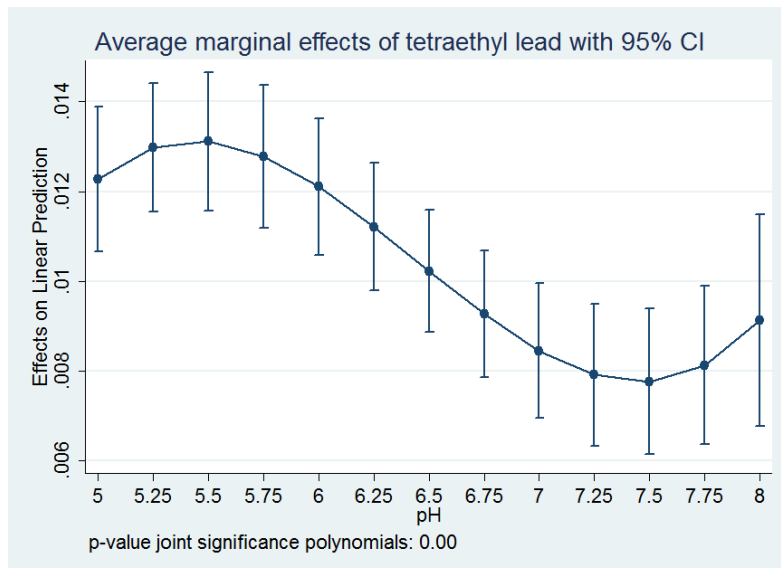
Figure 3: Average marginal effect of tetraethyl lead at different pH values

Marginal effects derived after regressing violent crime per capita in city centers on tetraethyl lead, tetraethyl lead x pH, tetraethyl lead x pH^2, and tetraethyl lead x pH^3.

Robust standard errors have been used clustered at city level. Marginal effects reported for value of pH between the 10th and 99th percentile. p-value joint significance

polynomials: p-value for the test of joint significance of the coefficients of the following regressors: tetraethyl lead x pH, tetraethyl lead x pH^2, and tetraethyl lead x pH^3.

For every city center, we combine data for the average pH level from the United States Geological Survey with crime observations from F.B.I.
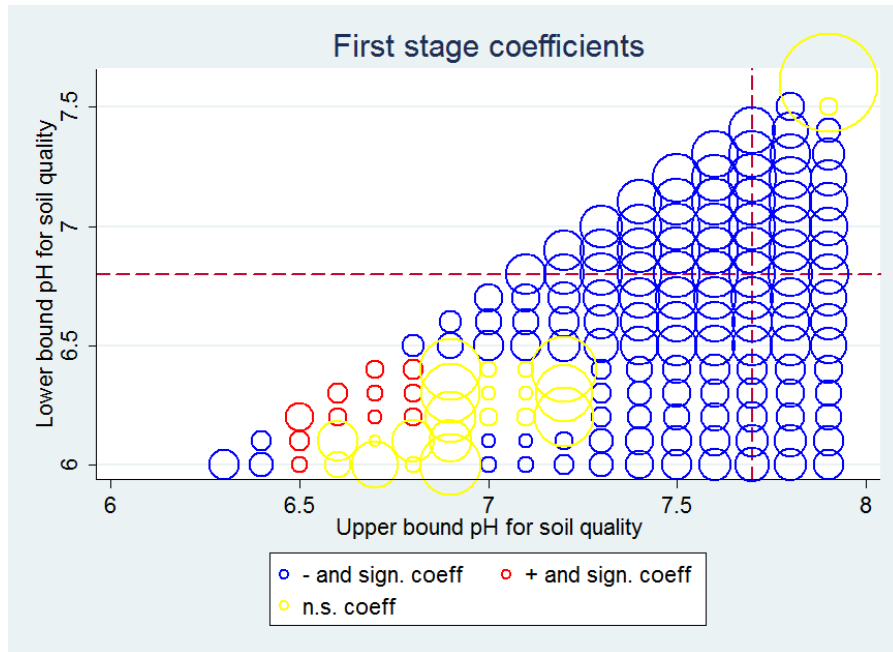
(a) Coefficients
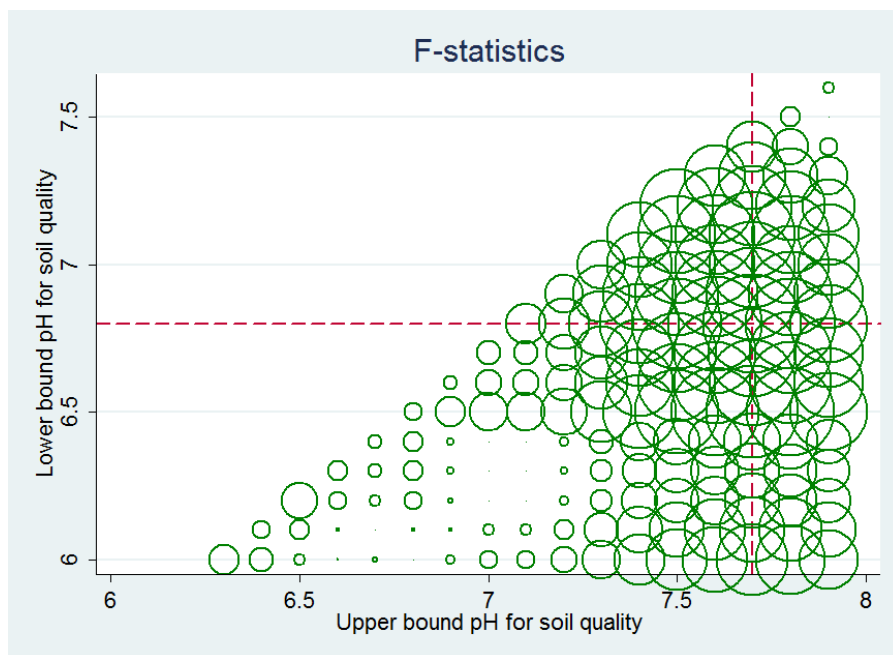
(b) F-statistics

Figure 4: Coefficients and F-statistics of the first stage regression for every possible pH interval

Panel a): Coefficients of first stage regression. Panel b): F-statistics of first stage regression. Coefficient and F-statistic of the excluded instrument derived after regressing violent crime per capita on city and year fixed effects and the interaction between tetraethyl lead 19 years before and the soil quality index. Every different circle refers to a different regression for every possible minimum and maximum level of pH. Robust standard errors have been used. The size of the circles refer to the absolute value of the coefficient or F-stat with respect to the coefficient or F-stat in the same category (- and sign.: negative and signficant, + and sign: positive and significant, n.s.: non significant). Dashed lines indicate our chosen soil quality index: pH between 6.8 and 7.7
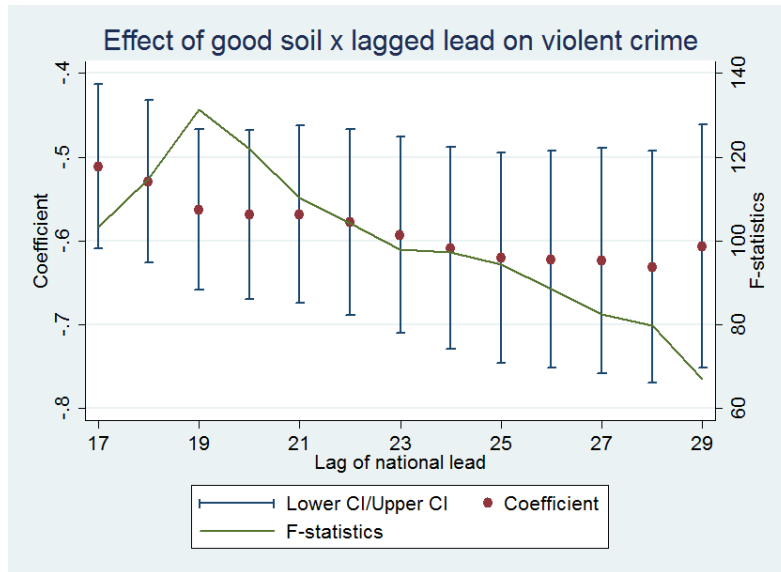
Figure 5: First stage using different lags of national lead poisoning

Left y axis: coefficient of the first stage estimate. Right y axis: F-statistics of the relevance of the instrument. For each possible lag of national lead (X), coefficient obtained

after regressing violent crime per capita in the city center on MSA, year and Census division times year fixed effects and the interaction between a dummy taking 1 if pH is

between 6.8 and 7.7 and the tonnes of lead consumed in U.S. as gasoline additive X years before, normalized by the maximum level of tetraethyl lead consumption.

F-statistics obtained as the F-statistics of the instrument in this regression.
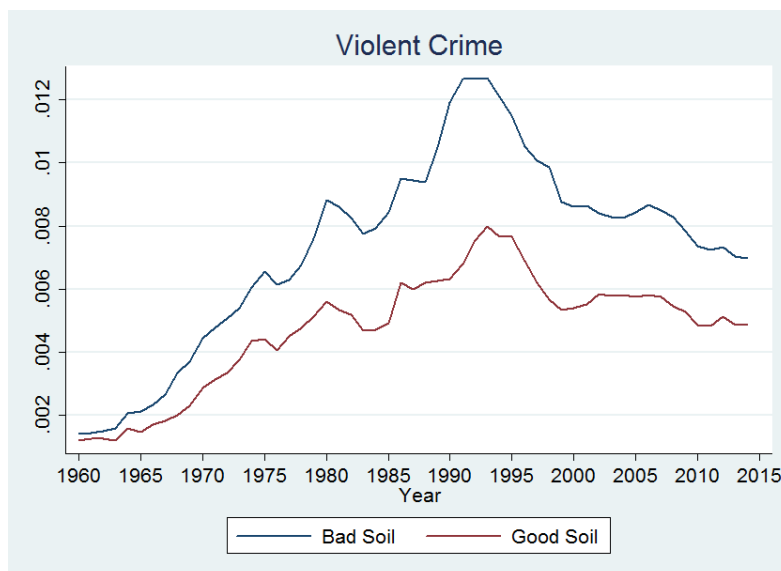
Figure 6: Time series of violent crime per capita in city center by good and bad soil

City centers with good soil: pH between 6.8 and 7.7. City centers with bad soil: pH outside the interval between 6.8 and 7.7.
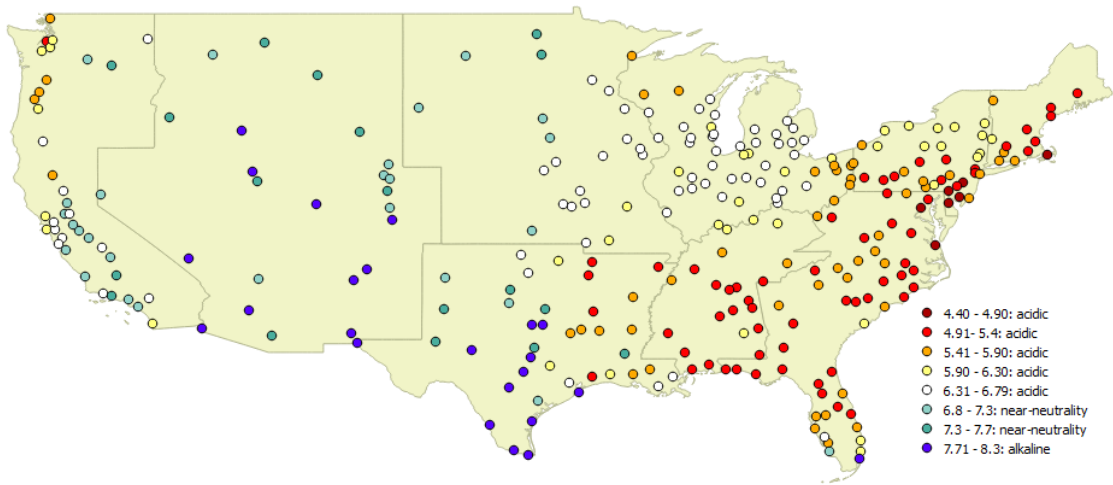
Figure 7: Map of city centers with good and bad soils for lead adsorption

City centers with good soil: pH between 6.8 and 7.7. City centers with bad soil: pH outside the interval between 6.8 and 7.7. The map reports the U.S. Census Divisions
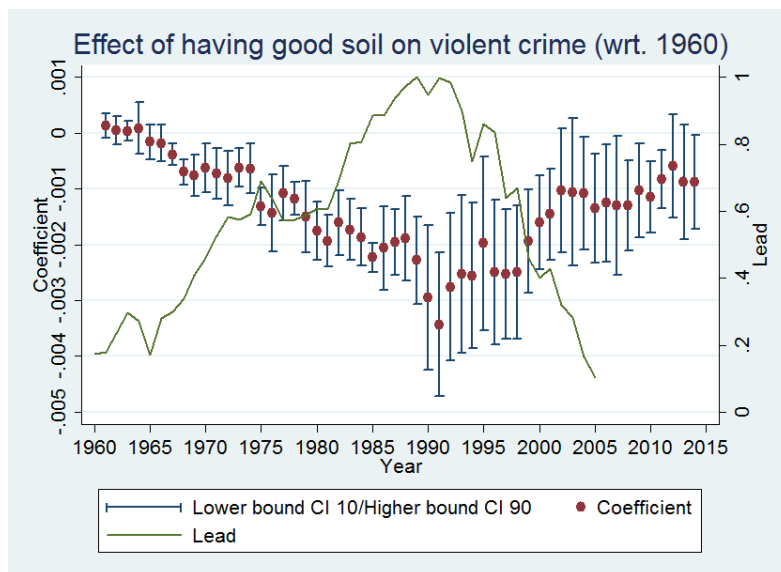
Figure 8: Time series of the effect of the good soil index on crime and time series of lagged tetraethyl lead

Coefficients obtained regressing violent crime per capita on the interaction between the good soil dummy and year dummies, controlling for city, year and Census division times year fixed effects. Standard errors have been clustered at Census Division level. Lower bound CI 10: lower bound confidence interval at 10 % significance level. Higher bound CI 10: higher bound confidence interval at 10 % significance level. City centers with good soil: pH between 6.8 and 7.7. Lead: tonnes of lead consumed in U.S. as gasoline additive 19 years before, normalized by the maximum level of tetraethyl lead consumption. 1960 year dummy has been omitted. Robust standard errors have been used. Left y axis: effect of the good soil index on crime. Right y axis: time series of lagged tetraethyl lead.
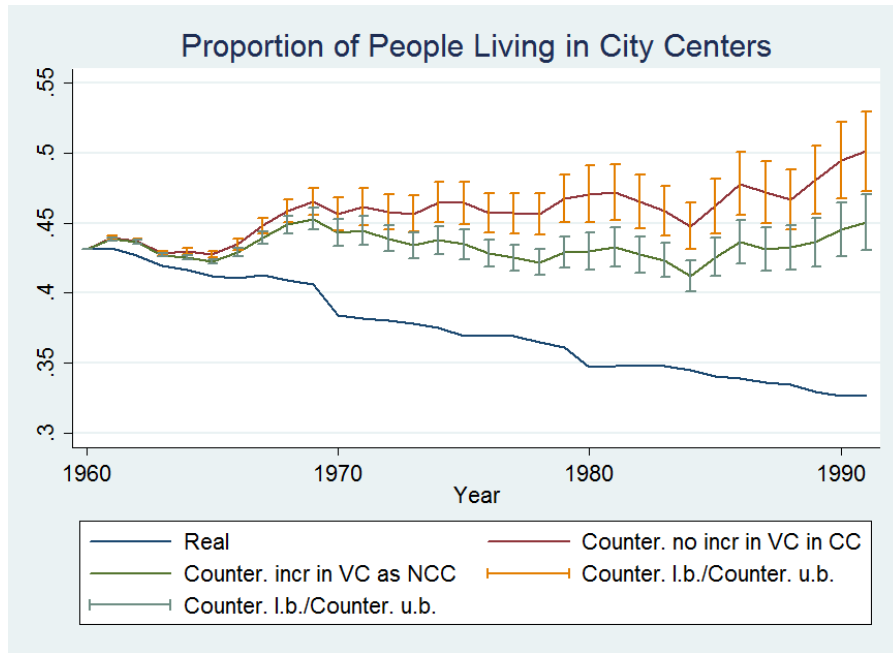
Figure 9: Counterfactual proportion of people in city center in MSA if violent crime in city center would not have increased from 1960 and if violent crime in city center would have increased from 1960 as in the suburbs

Real: actual time series of proportion of people in city center in MSA. Counter. no incr in VC in CC: counterfactual proportion of people in city center in MSA if violent crime (VC) in city center (CC) would not have increased from 1960 with corresponding 95 % confidence interval. Obtained subtracting the actual increase in violent crime from one year in the city center to another multiplied by the causal effect of crime on suburbanization from the actual suburbanization measure. Counter. incr in VC as NCC: counterfactual proportion of people in city center in MSA if violent crime in city center would have increased from 1960 as in the suburbs (NCC) with corresponding 95 % confidence interval. Obtained subtracting the actual difference in change in violent crime from one year to another in the city center with respect to the suburbs multiplied by the causal effect of crime on suburbanization from the actual suburbanization measure. VC: Violent crime per capita. CC (NCC): city center (suburbs). l.b: Lower bound confidence. u.b.: upper bound confidence.

43

9.2 Tables

Table 1: First stage using different fixed effects and time trends for all the years

VARIABLES	(1) Violent crime	(2) Violent crime	(3) Violent crime	(4) Violent crime	(5) Violent crime
Good soil x Lead	-0.00184***	-0.00528***	-0.00451***	-0.00327***	-0.00276***
	(0.000190)	(0.000326)	(0.000363)	(0.000378)	(0.000400)
Observations	9,515	9,515	9,484	9,484	9,363
R-squared	0.005	0.757	0.763	0.771	0.832
MSA FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
C. reg X Year FE	NO	NO	YES	NO	NO
C. div X Year FE	NO	NO	NO	YES	NO
State X Year FE	NO	NO	NO	NO	YES
Year	60-91	60-91	60-91	60-91	60-91
Estimation	OLS	OLS	OLS	OLS	OLS
F		262.16	154.46	74.80	47.78

For the notes see Table 2

Table 2: First stage using different fixed effects and time trends for Census Years

VARIABLES	(1) Violent crime	(2) Violent crime	(3) Violent crime	(4) Violent crime	(5) Violent crime
Good soil x Lead	-0.00206***	-0.00721***	-0.00556***	-0.00396***	-0.00325**
	(0.000611)	(0.00120)	(0.00134)	(0.00140)	(0.00145)
Observations	1,190	1,189	1,185	1,185	1,170
R-squared	0.004	0.744	0.752	0.758	0.831
MSA FE	NO	YES	YES	YES	YES
Year FE	NO	YES	YES	YES	YES
C. reg X Year FE	NO	NO	YES	NO	NO
C. div X Year FE	NO	NO	NO	YES	NO
State X Year FE	NO	NO	NO	NO	YES
Year	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90
Estimation	OLS	OLS	OLS	OLS	OLS
F		36.11	17.29	7.99	5.01

Violent crime: Violent crime per capita in the city center. Good soil x Lead: dummy taking 1 if pH in the city center is between 6.8 and 7.7 multiplied by tonnes of lead consumed in U.S. as gasoline additive 19 years before, normalized by the maximum level of tetraethyl lead consumption. C. reg: Census region. C. div: Census division fixed effects. CY: Census year. F: F-statistics on the excluded instrument. Robust standard errors have been used. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Balancing test for economic, social and geographic characteristics

Variable	Average	Levels		Trends	
		All US	**Inside Division**	**All US**	**Inside Division**
Area CC (50)	27.51	3.52	0.98	.	.
Area MSA (50)	2056.36	708.11	-424.82	.	.
Share Pop. CC (50 - 60)	0.47	0.09**	0.02	0.05**	0.01
Population CC (50 - 60)	2.0e+05	-7.7e+04	-1438.35	32129.34*	6486.92
Population MSA (50 - 60)	4.3e+05	-1.7e+05	1842.98	30009.88	40253.98
Pop. Density CC (50 - 60)	6109.20	-1535.46***	30.86	327.39	151.63
Pop. Density MSA (50 - 60)	197.35	-105.09***	-8.35	12.44	27.83
Violent Crime Rate CC (per 10000) (60 - 63)	13.82	-2.17	-0.34	-0.46	0.38
Murder Rate CC (per 10000) (60 - 63)	0.53	-0.11	0.01	-0.05	-0.04
Rape Rate CC (per 10000) (60 - 63)	0.70	0.06	-0.00	0.10	0.15
Robbery Rate CC (per 10000) (60 - 63)	4.71	0.43	-0.15	-0.27	0.19
Agg. Assault Rate CC (per 10000) (60 - 63)	7.89	-2.55**	-0.21	-0.29	0.08
Burglary Rate CC (per 10000) (60 - 63)	59.64	5.28	1.28	-0.54	-2.17
Larceny Rate CC (per 10000) (60 - 63)	169.71	78.02***	29.73	-10.26	-18.26*
Vehicle Theft Rate CC (per 10000) (60 - 63)	22.91	2.75	-1.78	0.24	-0.13
Total Crimes CC (per 10000) (60 - 63)	266.43	83.87***	28.82	-9.56	-17.52
Median Gross Rent (housing unit) MSA (60)	384.91	26.96**	22.12*	.	.
Median Single Family House Value MSA (60)	64628.31	4839.84*	2297.45	.	.
Median Family Income CC (50-60)	22811.72	1995.89***	1246.13*	87.89	-618.41
Median Family Income MSA (50-60)	21400.64	1837.63***	1236.50*	-319.70	-428.57
Annual Precipitation (77)	35.86	-19.38***	-8.86***	.	.
% Possible Sun (77)	59.93	7.91***	2.60	.	.
Average Jan Temp (77)	34.34	-1.49	-3.20	.	.
Average July Temp (77)	75.76	0.25	-0.12	.	.
% Blacks CC (60)	13.41	-7.81***	-1.21	.	.
% Blacks MSA (60)	9.45	-5.47***	-1.49	.	.
% Foreign CC (60)	16.40	-0.41	-0.70	.	.
% Foreign MSA (60)	14.47	0.70	-0.07	.	.
Distance Border or Coast	129.89	139.60***	35.60	.	.
Unemployment Rate MSA (60)	5.17	0.26	0.20	.	.
Labor Force Civilian MSA (50-60)	0.39	-0.01	0.00	0.00	-0.00
Emp. Rate MSA (50-60)	36.99	-1.18	0.26	0.21	-0.40
Emp. Rate Agriculture MSA (50-60)	3.44	0.57	0.54	-0.07	-0.01
Emp. Rate Business Services MSA (50)	2.29	0.50***	0.30**	.	.
Emp. Rate Construction MSA (50-60)	2.51	0.63***	0.19	-0.06	0.09
Emp. Rate Education MSA (60)	2.18	-0.02	-0.16	.	.
Emp. Rate Finance MSA (50-60)	1.17	0.15*	0.01	0.07*	0.03
Emp. Rate Government MSA (60)	1.82	0.29*	-0.03	.	.
Emp. Rate Manufacturing MSA (50-60)	9.18	-5.52***	-1.52**	0.82***	-0.04
Emp. Rate Mining MSA (50)	0.44	0.47	0.52	.	.
Emp. Rate Professional MSA (50)	3.53	0.10	-0.31	.	.
Median Age MSA (50-60)	29.49	-0.93*	-0.29	-1.01***	-0.39
% Over 65y MSA (50-60)	7.81	-0.94**	-0.64	-0.50*	-0.32
% Non-white MSA (50-60)	9.98	-5.17***	-1.77	0.50*	0.40
% Pub. Transportation to Work MSA (60)	6.82	-4.04***	-2.83***	.	.
Median Years of School MSA (50-60)	9.57	1.42***	0.69**	-0.13	-0.01
CC interstate rays (50-60)	0.04	-0.05**	-0.08*	0.17	-0.03
CC total rays (50-60)	0.04	-0.05**	-0.08*	0.17	-0.03
2-digit CC rays (50-60)	0.03	-0.03**	-0.05	0.20	-0.08
All interstate CC rays (50-60)	0.03	-0.03**	-0.05	0.22	-0.02
Federally funded CC rays (50-60)	0.02	-0.02	-0.03	0.26	-0.00
All rays in MSA (50-60)	0.06	-0.07***	-0.06	-0.08	-0.20
2-digit ray in MSA (50-60)	0.06	-0.07***	-0.05	-0.06	-0.23
Federally funded rays in MSA (50-60)	0.03	-0.03*	-0.06	0.11	-0.19
Rays in plan running through MSA	2.10	-0.24	-0.46*	.	.
Rays in plan running through CC	1.90	-0.01	-0.32	.	.

Years in parenthesis refer to first year in which the data are present and if a second number is present it represents the year in which the trend coefficient has been taken. Average: average value of the variable in the first year in which the variable is present. Levels, all U.S.: coefficient obtained regressing the variable in consideration on the good soil dummy. Levels, inside Division: coefficient obtained regressing the variable in consideration on the good soil dummy, controlling for Census Division fixed effects. Trend, all U.S.: coefficient obtained regressing the variable in consideration on the good soil dummy interacted by the year in which the trend coefficient has been taken, controlling for the interaction by the good soil dummy and the all the other years and omitting the interaction between the good soil dummy and the first year in which the variable is present. Trend, inside Division: coefficient obtained regressing the variable in consideration on the good soil dummy interacted by the year in which the trend coefficient has been taken, controlling for Census Division fixed effects interacted by year fixed effects, the interaction by the good soil dummy and the all the other years and omitting the interaction between by the good soil dummy and the first year in which the variable is present. Robust standard errors are always used. CC: city center. MSA: metropolitan statistical area. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Baseline results: The effect of crime on suburbanization

VARIABLES	(1) Share Pop CC	(2) Violent crime	(3) Share Pop CC	(4) Share Pop CC	(5) Share Pop CC	(6) ln(Pop CC)
Violent crime	-0.0165***		-0.0717***		-0.0843***	-0.257***
	(0.00141)		(0.0121)		(0.0167)	(0.0718)
Good soil x Lead		-0.914***		0.0686***		
		(0.0649)		(0.00885)		
Observations	9,481	9,484	9,481	9,716	9,481	9,484
R-squared	0.960	0.758		0.956	0.934	
MSA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
C. div x Year	NO	NO	NO	NO	YES	YES
Year	60-91	60-91	60-91	60-91	60-91	60-91
Estimation	OLS	OLS	IV	OLS	IV	IV
F	.	.	264.55	.	77.32	76.96

Share Pop CC: Proportion of MSA population living in city center. Violent crime: Violent crime per capita in the city center standardized. Good soil x Lead: dummy taking 1 if pH in the city center is between 6.8 and 7.7 multiplied by tonnes of lead consumed in U.S. as gasoline additive 19 years before, normalized by the maximum level of tetraethyl lead consumption. C. div: Census Division fixed effects. F: Cragg-Donald Wald F-statistics on the excluded instruments. Standard errors clustered at Census division times year level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: The effect of crime on population displacement

VARIABLES	(1) Log Pop MSA	(2) Log Pop CC	(3) Log Pop NCC	(4) Blacks MSA	(5) Blacks CC
Violent crime	0.0661	-0.257***	0.144***	0.137	4.730***
	(0.0428)	(0.0718)	(0.0534)	(0.809)	(0.795)
Observations	9,481	9,484	9,481	921	916
MSA FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
C. div x Year	YES	YES	YES	NO	NO
C. reg x Year	NO	NO	NO	YES	YES
Year	60-91	60-91	60-91	CY 60-90	CY 60-90
Estimation	IV	IV	IV	IV	IV
F	77.06	76.96	77.06	13.29	12.78

Violent crime: Violent crime per capita in the city center standardized. Pop MSA: Population in the MSA. Pop CC: Population in the city center. Pop NCC: Population in the suburbs. C. div: Census Division fixed effects. C. reg: Census Region fixed effects. F: Cragg-Donald Wald F-statistics on the excluded instruments. Standard errors clustered at Census division times year level (columns 1-3) and Census region times year level (columns 4-5) in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: The effect of crime on proportion of MSA employment in central city county

VARIABLES	(1) All	(2) Manuf	(3) Wholesale	(4) Retail	(5) Finance	(6) Other serv
Violent crime	-0.0108	-0.0462***	-0.0244*	-0.0386***	0.00283	-0.0285***
	(0.0113)	(0.0163)	(0.0143)	(0.0148)	(0.0178)	(0.0103)
Observations	5,334	5,334	5,334	5,334	5,334	5,334
MSA FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
C. div x Year	YES	YES	YES	YES	YES	YES
Year	74-91	74-91	74-91	74-91	74-91	74-91
Estimation	IV	IV	IV	IV	IV	IV
F	19.37	19.37	19.37	19.37	19.37	19.37

Violent crime: Violent crime per capita in the city center standardized. Dependent variable is proportion of MSA employment of SIC industry under consideration in county of the city center. All: all SIC employment. Manuf: Manufacturing; Wholesale: Wholesale Trade; Retail: Retail Trade; Finance: Finance, Insurance, And Real Estate; Other serv: Services). MSA with a unique county have missing values of employment proportion. C. div: Census Division fixed effects. F: Cragg-Donald Wald F-statistics on the excluded instruments. Standard errors clustered at Census division times year level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Timing of residential and employment decentralization

VARIABLES	(1) Share Manuf CC	(2) Share Manuf CC	(3) Share Pop CC	(4) Share Pop CC
Violent crime	-0.0241***	-0.0181	-0.0276***	-0.0478***
	(0.00863)	(0.0187)	(0.00631)	(0.0127)
Share Pop CC (10 years lag)		0.0656***		
		(0.0241)		
Share Manuf CC (10 years lag)				0.0256
				(0.0185)
Observations	5,352	5,332	5,367	2,344
MSA FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Good Soil x Lead 29 years lag	NO	YES	NO	YES
Year	74-91	74-91	74-91	74-91
Estimation	IV	IV	IV	IV
F	74.24	15.32	76.87	19.57

Violent crime: Violent crime per capita in the city center standardized. Share Pop CC: Proportion of MSA population living in city center. Share Manuf CC: proportion of MSA employment of manufacturing industry under consideration in county of the city center. MSA with a unique county have missing values of employment proportion. F: Cragg-Donald Wald F-statistics on the excluded instruments. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Profile of recent suburbanized population in 1980

Variable	Recent suburbanized	Difference wrt people staying in CC
Mean age	31.03	-2.86★★★
Mean number children	0.67	0.10★★★
Prop. married	0.62	0.09★★★
Prop. white	0.85	0.16★★★
Prop. black	0.11	-0.15★★★
Prop. high school or higher	0.63	0.14★★★
Prop. high school or higher of whites	0.64	0.11★★★
Prop. employed	0.55	0.11★★★
Prop. unemployed	0.03	-0.00★★★
Prop. people not working in CC	0.24	0.21★★★
Mean occupational score	18.69	4.18★★★

Prop.: Proportion. Recent suburbanized refers to people who in 1980 lives in a not central city in the metropolitan area and in the previous five years they were living in the central city of the same metropolitan area. Difference with respect to people staying in CC has been obtained regressing the variable under interested on a variable indicating whether the person is a recent suburbanized or he continues to live in the central city for the sample of people living in metropolitan areas. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneous effects of correlation between crime rates and proportion blacks living in city center

VARIABLES	(1) Violent crime
Prop. Blacks CC	0.000379***
	(8.11e-05)
Prop. Blacks CC x Rays CC	-3.10e-05**
	(1.10e-05)
Prop. Blacks CC x Rays CC x Lead	4.90e-05***
	(9.02e-06)
Observations	916
R-squared	0.798
MSA FE	YES
Year FE	YES
C. reg X Year FE	YES
Year	CY 60-90
Estimation	OLS

Violent crime: Violent crime per capita in the city center. Prop. Blacks CC: proportion of black population in city center in the MSA. Rays CC: number of highway rays passing through the city center, source: Baum-Snow (2007). Lead: tonnes of lead consumed in U.S. as gasoline additive 19 years before, normalized by the maximum level of tetraethyl lead consumption. C. reg: Census region fixed effects. CY: census years. Standard errors clustered at Census region times year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10: Effect of interaction good soil and different lag of past leads on education outcomes and crime

VARIABLES	(1) Share high school	(2) Share high school
Good soil x Lead (9 years before)	-0.546	-0.546
	(0.708)	(1.860)
Good soil x Lead (19 years before)	0.699	0.699
	(1.895)	(4.270)
Good soil x Lead (29 years before)	-9.485***	-9.485
	(2.132)	(5.846)
Observations	1,174	1,174
R-squared	0.979	0.979
MSA FE	YES	YES
Year FE	YES	YES
C. reg x Year	YES	YES
Year	CY 60-90	CY 60-90
Estimation	OLS	OLS
s.e. cluster	MSA	C. reg x Year

Violent crime: Violent crime per capita in the city center. Share high school: share of population with high school diploma in the MSA. Good soil x Lead (X years before): dummy taking 1 if pH in the city center is between 6.8 and 7.7 multiplied by tonnes of lead consumed in U.S. as gasoline additive X years before, normalized by the maximum level of tetraethyl lead consumption. CY: Census years. C. reg: Census region fixed effects. CY: census years. s.e. cluster: cluster level of the standard errors. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Results controlling for different lagged effect of education level

VARIABLES	(1) Share pop CC	(2) Share pop CC	(3) Share pop CC
Violent crime	-0.0591***	-0.0781***	
	(0.00678)	(0.0289)	
Good soil x Lead (29 years before)		-0.0166	
		(0.0208)	
Share high school MSA			-0.0105**
			(0.00426)
Observations	9,481	9,481	939
MSA FE	YES	YES	YES
Year FE	YES	YES	YES
C. reg x Year FE	YES	YES	YES
Year	60-91	60-91	CY 60-90
Estimation	IV	IV	IV
F	156.25	5.52	50.54

For the notes see Table 12. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 12: Results controlling for instrumented education level

VARIABLES	(1) Sh. pop CC	(2) V. crime	(3) Sh. pop CC	(4) H.s. MSA	(5) V. crime	(6) Sh. pop CC	(7) H.s. MSA	(8) V. crime
Violent crime	-0.0686***		-0.0611***			-0.0827***		
	(0.0214)		(0.0120)			(0.0232)		
Share high school MSA			-0.00183			0.000998		
			(0.00198)			(0.00245)		
Good soil x Lead		-0.957***		-7.135***	-1.024***		-7.008***	-1.018***
		(0.192)		(1.906)	(0.211)		(1.964)	(0.213)
H.s. U.S. x age school entry				0.0131***	-0.00259**			
				(0.00164)	(0.000899)			
H.s. U.S. x age school leave							0.00713***	-0.000962*
							(0.00116)	(0.000544)
Observations	1,184	1,185	917	935	1,181	917	935	1,181
MSA FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
C. reg x Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Year	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90
Estimation	IV	OLS	IV	OLS	OLS	IV	OLS	OLS
F	17.51	.	12.24	.	.	7.97	.	.

Sh pop CC: Proportion of MSA population living in city center. V. crime: Violent crime per capita in the city center standardized. Good soil x Lead: dummy taking 1 if pH in the city center is between 6.8 and 7.7 multiplied by tonnes of lead consumed in U.S. as gasoline additive 19 years before, normalized by the maximum level of tetraethyl lead consumption. Share high school MSA: Percentage of people with high school diploma in the MSA. H.s. U.S.: Percentage of people with high school diploma in the U.S. Age school entry: state age school of entry in 1910. Age school leave: State minimum age school leave in 1910. C. reg: Census Region fixed effects. CY: Census Year. F: F-statistics on the excluded instruments. Stock-Yogo weak ID test critical value at 10% maximal IV size: 7.03. Standard errors clustered at Census region times year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13: Effect of violent crime on MSA population, house prices, and income

VARIABLES	(1) Pop. MSA	(2) H. rent MSA	(3) H. price MSA	(4) Inc MSA	(5) Inc MSA
Violent crime	95,144	57.94***	21,690**	3,422**	836.2*
	(68,244)	(16.58)	(8,838)	(1,252)	(449.5)
Observations	921	921	920	921	917
MSA FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
C. reg x Year	YES	YES	YES	YES	YES
Year	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90
Controls	.	.	.	.	Education
Estimation	IV	IV	IV	IV	IV
F	13.29	13.29	13.41	13.29	12.24

Violent crime: Violent crime per capita in the city center standardized. Pop MSA: Population in the MSA. H. rent MSA: Median gross rent per housing unit in the MSA. H. price MSA: Median single family house value. Inc MSA: Median family income in the MSA. Control for education: control for the percentage of people with high school diploma in the MSA instrumented by the state age school of entry in 1910 multiplied by the overall percentage of people with high school diploma in the U.S. CY: Census years. C. reg: Census Region fixed effects. F: F-statistics on the excluded instruments. Standard errors clustered at Census region times year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 14: Effect of violent crime on MSA inequalities and transportation

VARIABLES	(1) Gini MSA	(2) Inc CC/MSA	(3) Inc CC	(4) Highway CC	(5) Pub transp MSA
Violent crime	0.00613**	-0.0945***	-358.3	0.255*	-2.212**
	(0.00243)	(0.0210)	(1,394)	(0.135)	(0.946)
Observations	921	921	921	921	921
MSA FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
C. reg x Year	YES	YES	YES	YES	YES
Year	CY 60-90	CY 60-90	CY 60-90	CY 60-90	CY 60-90
Estimation	IV	IV	IV	IV	IV
F	13.29	13.29	13.29	13.29	13.29

Violent crime: Violent crime per capita in the city center standardized. Inc CC/MSA: ratio between the median family income in the city center (CC) and the median family income in the MSA. Inc CC: median family income in the city center. Gini MSA: Simulated Gini coefficient from Baum-Snow (2007). Pub trans MSA: percentage of people using public transport to get to work. Highway CC: highway rays built passing through city center. CY: Census years. C. reg: Census Region fixed effects. F: F-statistics on the excluded instruments. Standard errors clustered at Census region times year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15: Elasticities of house rents, income and population with respect to violent crime

VARIABLES	(1) Log h. rent MSA	(2) Log income MSA	(3) Log Pop. MSA
Log violent crime	0.193**	0.157*	0.145
	(0.0836)	(0.0880)	(0.141)
Observations	918	918	918
R-squared	0.830	0.838	0.990
MSA FE	YES	YES	YES
Year FE	YES	YES	YES
C. reg x Year	YES	YES	YES
Year	CY 60-90	CY 60-90	CY 60-90
Estimation	IV	IV	IV
Cluster s.e.	MSA	MSA	MSA
F	11.69	11.69	11.69

H. rent MSA: Median gross rent per housing unit in the MSA. Income MSA: Median family income in the MSA. Pop. MSA: Total population in the MSA. Violent crime: Violent crime per capita in the city center standardized. C. reg: Census Region fixed effects. CY: Census Year. F: F-statistics on the excluded instruments. Standard errors clustered at Census region times year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: Elasticities of amenities and productivity with respect to violent crime

			Control for mediation	
Coefficient	None	Highways	Resid suburbanization	Empl centralization
λ^θ	-0.0991**	-0.0972**	-0.1068**	-0.164
	(0.04551)	(0.04371)	(0.04552)	(0.6082)
λ^A	0.1243**	0.1219**	0.1260**	0.1887
	(0.05242)	(0.04991)	(0.05111)	(0.62977)

λ_θ: elasticity of city amenities with respect to violent crime. λ_A: elasticity of city productivity with respect to violent crime. Control for mediation, highways: the estimated regression also includes the number of highways passing through the MSA. Control for mediation, resid suburbanization: the estimated regression also includes the proportion of population in MSA living in city center. Control for mediation, empl centralization: the estimated regression also includes the proportion of employment in MSA located in the central county. Standard errors have been bootstrapped: this strategy consists in first bootstrapping a panel sample from our distribution of observations; subsequently, we have estimated the elasticity of house prices, income and population to violent crime and then compute the corresponding elasticity of amenities and productivity to violent crime; we have replicated this procedure several times and obtained a distribution of these parameters and relevant standard errors. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1