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The Decaying American Dream: Violent Crime, Neighbourhoods and Intergenerational Mobility in the United States

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Declaration

I declare that the content of this thesis is my own work and that, to the best of my knowledge, it contains no material published or written by any other author or authors, except where acknowledged. This thesis has not been submitted for award of any other degree or diploma at the University of New South Wales or any other educational institution.

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22$^{\text{nd}}$ November, 2019

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To the reader, enjoy.

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Abstract

In this thesis I study the effect of violent crime as the primary driver of neighbourhood decay on intergenerational mobility in the United States. By drawing on evidence that links lead poisoning to violent crime and soil quality with the bioavailability of lead to humans, I use soil pH levels of city centres to exogenously predict differences in neighbourhood quality. Cities with neutral soil experienced low historical exposure to lead and as a result, low violent crime and neighbourhood decay. I find men who grow up in cities with low levels of neighbourhood decay have between 2 and 3 percentage points higher intergenerational mobility ranks relative to their peers raised in families with the same income but in decaying cities. I also show decay in cities has important implications for racial disparities in intergenerational mobility, where white males disproportionately enjoy the benefits of living in a city with low neighbourhood decay. In these cities, the racial gap in mobility is up to 40% higher and is the widest for the very poor. Mechanism analysis finds racial gaps in intergenerational mobility are driven by racial segregation and suburbanisation in cities with high crime and incarceration. Whites appear to be sorting into low crime suburban areas leaving blacks in high crime city centres. The results of this thesis suggest urban disamenities including crime and associated lack of economic opportunity significantly contribute to persistent gaps in intergenerational mobility in American cities.

Chapter 1

Introduction

The prevalence and visibility of poor upward mobility in the United States (U.S.) increasingly threatens the attainability of the classic American dream of economic success. The modern American dream is characterised by the presence of substantial heterogeneity in intergenerational mobility between U.S. cities, suggesting that location of residence is influential in shaping long run outcomes of residents (Chetty et al., 2018a; Chetty & Hendren, 2017b). Two children born into an equally low income household from two different cities can have vastly different incomes in adulthood. In 2015, a child born into a family income of $27,000 who grew up in Billings County, North Dakota was expected to earn $41,000, while a child with the same family income who grew up in Johnson County, Tennessee earned only $16,000 as an adult (Chetty et al., 2018a). This disparity in upward mobility across the U.S. indicates that the place in which a child grows up in is highly predictive of future labour market outcomes.

One of the most striking features of poor intergenerational mobility in the U.S. is the large racial disparities in income mobility that seem to persist over time (Chetty et al., 2018b; Collins & Wanamaker, 2017). Black Americans consistently struggle the most in escaping the bottom of the income distribution in comparison to white Americans (Akee, Jones & Porter, 2019). In 2017, the median black American earned close to $28,000 less than the median white person (U.S. Department of Commerce, 2018). Intergenerational mobility outcomes that are heterogeneous by race may thus be a signal of underlying unequal economic opportunities.

While significant differences in mobility both between and within neighbourhoods exist, there has been limited research to date on what has caused these differences. In this thesis I explore one channel through which intergenerational mobility differences exist and persist today: the development of different neighbourhoods. Disparities in opportunities available to residents across neighbourhoods in the U.S. can explain the differences in mobility across space. In this thesis, I argue that high violent crime in a city sparks the destruction of neighbourhood amenities and public goods, reducing investment into neighbourhoods and limiting economic opportunities available to its residents.

As the transmission of earning capacity from parent to child is conditional on the economic opportunities present to both parents and their children, the decay of economic opportunities in a neighbourhood is harmful across generations. A history of high violent crime in a neighbourhood can reduce the quality of schools, hospitals or work choices, and increase the probability of arrest or incarceration. This reduction in neighbourhood amenities can also have differential effects by race. Black Americans are disproportionately the subject of targeted policing and mass incarceration and have poorer education and health outcomes than the general U.S. population (Liu, 2019; Legewie & Fagan, 2019). I explore the effect of violent crime on intergenerational mobility through neighbourhood-level mechanisms that differentially affect racial groups.

To exogenously identify the effect of violent crime on intergenerational mobility, I use a proxy for lead exposure that predicts violent crime in U.S. city centres. Lead is an environmental neurotoxicant that can cause long term behavioural problems including impulsiveness and aggression when exposure occurs at a young age (Mason, Harp & Han, 2014). I exploit the link between lead exposure and violent crime as identified in the medical and health literature, which states that the effect of lead on offending occurs with a time lag (Nevin, 2007). Young children in the first two years of life, who are the most vulnerable to the harmful effects of lead, are expected to reach peak criminal propensity at around 19 years old. I show that this time lag in the lead-crime relationship motivates the relevance of my identification strategy, where the historic peak in violent crime across U.S. cities occurs in 1991, preceded by the peak in national lead consumption in 1972, 19 years prior.

From the end of World War II, the most common source of lead in the U.S. was gasoline in the form of tetraethyl lead. Leaded gasoline emissions were released into the air as the U.S. experienced a boom in ownership of automobiles. These leaded emissions were then absorbed by the soil in the environment. Soil that is closest to neutrality is least likely to retain lead when absorbed, reducing the likelihood of human lead poisoning upon ingestion or inhalation. I exploit soil pH levels as a measure of lead's bioavailability in soil. Soil pH is time-invariant and exogenously determined making it an ideal cross-sectional proxy for lead exposure. In line with chemical literature, I define a city with a neutral pH level, that is between 6.8 and 7.7, as a good soil city intended to be treated with low violent crime, and a bad soil city treated with high crime as one with a pH outside of these values. Bad soil cities are intended to have high lead exposure during the treatment period, which I define as 1960 onwards, 19 years after the massive rise in leaded gasoline consumption.

I first show soil pH has an effect on my outcome of interest, intergenerational mobility. Next I show that soil pH influences other neighbourhood outcomes as evidence in favour of lead triggering a process of neighbourhood decay in a city. I then use this unique instrumental variable (IV) previously used by Curci and Masera (2019) to exogenously predict a history of violent crime in a city centre. U.S. cities experienced different violent crime trajectories because of different lead exposure levels, and I exploit cross-sectional variation in soil pH to assess the impact of these differential trends in violent crime on income mobility.

Consistent with Curci and Masera (2019), I show the effect of lead on crime is higher in cities with bad soil, or soil that contains highly bioavailable lead. Cities with good soil have double the violent crime rate of cities with bad soil in 1991 when national rates of violent crime reach an historic peak. I show that cities have similar trends in violent crime in 1960, before lead's effect started, as evidence against differential pretreatment trends in crime. Further, city centres have very little differences in their crime rates today. I then conduct a balancing test of both levels and trends to compare cities in their observable socioeconomic and demographic characteristics prior to the increase in lead consumption. As I do not observe mobility estimates prior to the shock in violent crime, this balancing test provides evidence that cities were similar across other variables that may also affect mobility.

I aggregate Census tract level outcomes using 2014-15 estimates of mobility for children in their mid-thirties compiled by Chetty et al. (2018a) to the Census place level to create a new database of 302 U.S. cities. I present reduced form effects as my main results as evidence that soil pH, a proxy for lead poisoning, sparked a process of neighbourhood decay in cities with poor mobility today. Results here show children who live in good soil cities have between 2 and 3 percentage points higher mobility ranks relative to children who have the same parental income but live in bad soil cities. Interestingly, when comparing individuals to their same-race peers, soil pH significantly affects the mobility of white men only. Exposure to good neighbourhoods does not appear to differentiate the earnings of black men relative to each other, which suggests that race alone is an important predictor of income mobility.

I then estimate the black-white gap in mobility using my reduced form model and find that black men have between 9 and 12 percentage points lower mobility ranks across all income levels compared to white men. This striking result confirms previous work that finds a 10 percentile gap in black-white mobility ranks of men (Chetty et al., 2018b). Importantly, I also find the racial gap in intergenerational mobility is 20% to 40% higher in good soil neighbourhoods, and this racial gap is most prominent amongst the very poor. White men raised in areas with low rates of decay have higher mobility outcomes while black men do not enjoy these same benefits, which widens the racial gap in income mobility within a city. These results suggest that exposure to good neighbourhoods may not alleviate the economic burden black men face in achieving labour market equality if whites tend to disproportionately benefit from city amenities.

Next I identify which aspects of a neighbourhood are most affected by lead exposure by estimating the effect of soil pH on other neighbourhood-level outcomes. I show that soil quality has an effect on racial segregation, suburbanisation, incarceration, arrest rates, policing, high school education, property values and marriage rates. I find limited evidence however that soil pH influences college education levels or unemployment rates. I use these associations between lead and neighbourhood outcomes to later identify potential mechanisms driving the estimated changes in intergenerational mobility.

Violent crime is the primary causal mechanism that influences intergenerational mobility of residents in a neighbourhood. I study the crime-mobility relationship using soil pH as an instrument for violent crime. IV results show that increasing violent crime by one standard deviation across the period 1978 to 2014 decreases average mobility ranks by between 5 and 7 percentage points. Furthermore, the elasticity of intergenerational mobility ranks in response to a crime shock is highest for poor, white children, decreasing their mobility estimates by up to 8 percentage points.

After finding a strong causal effect of violent crime, I distinguish other non-causal mechanisms that may be contributing to poor intergenerational mobility in American cities. I do this because limitations with the exclusion restriction imply that IV results represent both the direct and indirect effect of violent crime on mobility. I find associational evidence that shows racial segregation in suburbanised cities combined with high incarceration and arrest rates are the strongest mediators of the crime-mobility relationship. Racial gaps in intergenerational mobility are driven primarily by racial sorting into neighbourhoods, with whites living in low crime suburban areas and blacks living in high crime city centres. Results here suggest that high crime in black neighbourhoods ex-post predicts areas prone to low upward mobility. There is limited evidence to suggest other variables studied are mediating the crime-mobility relationship.

Furthermore, I examine potential threats to identification by testing the potential direct effect of lead on non-violent crimes. I conduct a placebo test to show that lead is not predictive of property crime rates. As expected, lead exposure only affects violent crime patterns largely due to their impulsive and aggressive nature. Further, I provide evidence for the exclusion restriction by showing that my instrument, soil pH, does not affect mobility directly by influencing either cognitive abilities or agricultural production. Finally, I test an alternative definition of good soil using the continuous soil pH variable and find similar results to using the binary definition.

My results complement growing evidence on the effect of neighbourhoods on intergenerational mobility (Chetty et al., 2017a; Chetty & Hendren, 2017b; Chetty, Hendren & Katz, 2016). My primary contribution is to show that neighbourhood decay caused by lead exposure is a significant driver of intergenerational mobility differences across U.S. cities. Furthermore, I show that environments characterised by lead and associated urban disamenities can produce long run effects on labour market outcomes.

Using a new source of cross-sectional variation in soil quality as a unique instrument to inform my causal identification strategy, I explain violent crime as the primary channel mediating differences in mobility across U.S. cities. My analysis of mechanisms shows that cities with high lead exposure, violent crime and share of black residents combined produce the worst intergenerational mobility outcomes. Furthermore, I also confirm prior research that finds large racial disparities in earnings that persist across generations (Chetty et al., 2018b; Collins & Wanamaker, 2017). My results have implications for income inequality in the U.S. and for the welfare of future generations growing up in decaying urban cities.

More generally, my thesis relates to studies on the biological determinants of violence and crime. I contribute to medical and public health studies to show that lead as an environmental neurotoxicant can have decaying effects on neighbourhood-level outcomes through increasing violent criminal tendencies. Finally, my thesis provides hopeful evidence that may inform future neighbourhood investment initiatives, public health policy surrounding lead removal, and crime reduction.

Chapter 2

Literature Review

2.1 Intergenerational mobility

Poor intergenerational mobility is increasingly prevalent in communities across the U.S., with an increasing body of literature highlighting the causal effect of place in determining intergenerational mobility outcomes (Corak, 2013; Sharkey, 2016; Chetty & Hendren, 2017a). The places in which children grow up in have been shown to significantly impact decisions and behaviour in adulthood (Chetty et al., 2018a).

The impact of neighbourhoods on the outcomes of children can be seen in social experiments involving public housing. Chyn (2018) finds that public housing demolition in Chicago that forces families to move out of concentrated disadvantage and into low poverty areas through the use of housing vouchers improves the long run outcomes of children, including an increase in their incomes and likelihood of being employed as an adult relative to their non-displaced peers.

Chetty, Hendren and Katz (2016) also study the long term effects of moving to a low poverty neighbourhood at a young age through an evaluation of the Moving to Opportunity program, a social experiment conducted in the mid-1990s in Baltimore, Boston, Chicago, Los Angeles and New York. They find that moving to a low poverty neighbourhood before the age of 13 increases college attendance and earnings as an adult. Children who moved had incomes that were over $3,400 higher than their control counterparts. Further, children who moved into lower poverty areas were also more likely than those that did not to continue living in good neighbourhoods as adults and were less likely to become single parents.

Longer exposure to better neighbourhoods earlier in life improves economic outcomes in adulthood (Deutscher, 2019). By exploiting variation in the timing of children moving across commuting zones, Chetty and Hendren (2017a) find that the outcomes of children who move to an area with a higher average income converge to the outcomes of original residents in the same birth cohort. The authors provide evidence in favour of the causal effect of place, with urban areas heavily concentrated in poverty generating negative outcomes for all low income children. This place effect however seems to amplify existing racial inequalities, where black children who grow up in poor neighbourhoods have worse economic outcomes relative to their white counterparts.

Substantial heterogeneity in mobility outcomes across groups of people within the same geographical area have been identified in the literature, with the largest intergenerational mobility gaps previously found for African American men (Chetty et al., 2018b; Akee, Jones & Porter, 2019). Black Americans have had substantially lower rates of upward mobility since 1880 compared to white Americans, contributing to large racial disparities in income that have persisted across generations (Collins & Wanamaker, 2017). White Americans also tend to occupy a disproportionate share of top income earners, while African Americans, along with American Indians and Hispanics, are consistently at the bottom of the total income distribution in the U.S. (Akee, Jones & Porter, 2019).

Chetty et al. (2018b) provide strong evidence of a racial gap in mobility outcomes that is especially prevalent for men. They estimate that the black-white gap in income rank for males is 10 percentiles. The authors find that while black and white women have similar income experiences, the black-white income gap for men is highly pertinent, with black men also experiencing high rates of high school dropout and incarceration.

These disparities in earnings seem to be a function of both places and the distribution of people living in those places, which is indicative of both between and within neighbourhood variations in mobility. Importantly, disparities in income seem to persist across generations, which suggests some underlying mechanism that contributes to this persistence. The mechanisms that contribute to the persistence of poor mobility have been poorly studied.

2.2 Neighbourhood decay and violent crime

Neighbourhood decay can be defined as the formation or destruction of amenities and public goods that shape the current and future economic opportunities of residents in a city. Neighbourhood characteristics, which may be an indicator of neighbourhood decay, have been found to be a major contributing factor to individual mobility paths (Chetty et al., 2018a; Chetty & Hendren, 2017b). Various aspects of neighbourhoods that have formed over time, including for example the development of educational systems and labour market structures, contribute to the economic outcomes of parents, and in turn, their children. A shock to violent crime that triggers a process of neighbourhood decay reduces the amenity value of a city, decreasing investment into the neighbourhood and reducing economic opportunities, which in turn can affect long run outcomes of residents.

A history of high violent crime in a neighbourhood increases the likelihood of direct exposure to violence across generations. Direct exposure to violent crime as a child increases an individual's likelihood of becoming an offender themselves. By exploiting the quasi-random assignment of refugee immigrants to neighbourhoods in Denmark, Damm and Dustmann (2014) find that high crime neighbourhoods foster more criminals, with exposure to a high share of violent offenders before the age of 15 increasing the likelihood of criminal conviction for men.

Sviatschi (2019) shows that exposure to the illegal drug market increases a child's criminal tendencies, with children directly involved in the production of cocaine in Peru 30% more likely to be incarcerated for violent and drug-related offences as adults. Sviatschi's (2019) findings suggest that exposure to illegal markets fosters the accumulation of human capital specific to the illegal industry, generating greater engagement in criminal behaviour as an adult.

Exposure to deviant peers within neighbourhoods also increases youth criminal behaviour. Billings, Deming and Ross (2016) find that individuals of the same race and gender who live near each other and attend the same school are more likely to be arrested for having committed the same crime together. By using exogenous variation in school boundaries, the authors find that concentrating disadvantaged youth together in the same neighbourhood increases crime, which is evidence for peer effects contributing to youth crime.

Direct exposure to crime as a child reduces learning and academic performance. Exposure to frequent violence has been found to negatively affect test scores for children in Chicago due to disruptions to learning (Burdick-Will, 2013). Children interviewed within a week of a homicide that occurred near their home exhibited lower levels of attention and impulse control, and their parents reported greater distress, while exposure to a local homicide before a cognitive assessment has been found to reduce performance substantially, specifically for African American children (Sharkey et al., 2012; Sharkey, 2010). Another study reported that children who lived within close proximity to a sniper attack experienced declines in third and fifth grade test scores (Gershenson & Tekin, 2018). Reductions in school performance due to exposure to crime events may be due to short term disruptions to learning or long term persistence of stress or fear. Large racial gaps in feelings of safety at school have also been identified in New York City, with Black and Hispanic students more likely to report feeling unsafe at school than White and Asian students (Lacoe, 2015).

A growing body of evidence suggests that disadvantaged children are more sensitive to shocks in the home environment including the trauma of parental incarceration. Exploiting random judge assignment, Dobbie et al. (2018) find that incarceration of a parent during childhood significantly increases teen crime and pregnancy rates and decreases employment at age 20, particularly for the most disadvantaged children in Sweden. Furthermore, Liu (2019) exploits exogenous changes in sentencing policies across states and years in the U.S. to find increases in single-mother households and decreases in the likelihood of college education are associated with the rise of mass imprisonment of African American men since the 1970s. Further, the black-white income gap is wider for men who lived in areas with harsher sentencing policies during childhood.

Moreover, closest to my research, Sharkey and Torrats-Espinosa (2017) instrument the timing of law enforcement grants to predict crime rates and find that a one standard deviation decline in violent crime in adolescence increases expected income ranks in adulthood by at least 2 points among individuals with parents at the 25th percentile of the income distribution. Further, neighbourhoods in Chicago characterised by high levels of violence, incarceration, and lead exposure have also been found to be predictive of lower income ranks and higher incarceration rates of black men (Manduca & Sampson, 2019). This literature indicates that toxic neighbourhood environments characterised by violence and crime influence intergenerational mobility in the U.S..

2.3 Lead and its effects

Lead (symbol Pb) is a naturally occurring heavy metal and an environmental neurotoxicant that when ingested or inhaled at a young age, particularly before the age of five or prenatally, significantly affects neurological and cognitive functioning. Lead's concentration in blood and accumulation in bone causes damage to the nervous system and brain by mimicking the effects of calcium and interfering with neurotransmitter release (Mason, Harp & Han, 2014). Young children are particularly susceptible to the permanent effects of lead poisoning as they are not only more likely than older children and adults to ingest lead but their rapidly developing young brains and nervous systems are especially vulnerable to chemical toxicity (Lanphear, 2015).

Lead exposure has been linked to a range of long term developmental and behavioural problems, including deficits in intelligence, memory, learning, emotional processing, executive functioning and attention (Mason, Harp & Han, 2014). One meta-analysis of 33 studies showed that lead is significantly associated with the attention deficit hyperactivity disorder symptoms of inattention and impulsiveness (Goodlad, Marcus & Fulton, 2013). Damage to neurotransmitter functioning caused by lead disrupts impulse control that can lead to anti-social problems including violent and impulsive offending. Further, psychological and neurological research finds that impulsive people are more likely to show deficits in learning-based decision-making and are more likely to become repeat offenders (Franken et al., 2008; Aharonia et al., 2013).

Historically, lead has been found in water pipes, lead-based paint and gasoline, and currently still found in imported children's toys and older houses. The use of lead-based paint in residential housing was banned in the U.S. in 1978 and the leaded gasoline phasedown began in 1975 with the U.S. Clean Air Act, culminating in its prohibition in 1996. Blood lead levels (BLLs) declined by almost 80% from 1978 to 1991 during this period of leaded gasoline phasedown (Dapul & Laraque, 2014). The decline in lead levels observed from the mid-1970s combined with the decline in crime witnessed since the mid-1990s is indicative of some association between lead and crime. Despite the decline in elevated BLLs in American children, lead continues to pose a public health threat through its impact on behaviour amongst adults who were previously exposed as children and the continued low-level exposure amongst low income and minority households[1].

The heterogeneous impacts of lead imply that poor and minority children not only have greater exposure but are more vulnerable to the damaging effects of lead (Aizer et al., 2018). Disadvantaged children are also more likely to live in urban environments which increases the likelihood of contact with lead due to greater traffic congestion, proximity to highways and older housing (Aizer & Currie, 2017). Children born into disadvantaged households who grow up in homes built before the 1970s and are of racial and ethnic minority backgrounds have higher BLLs (Dapul & Laraque, 2014). Importantly, large racial disparities in lead toxicity exist, with low income black communities disproportionately exposed to and harmed by lead (Sampson & Winter, 2016; Muller, Sampson & Winter, 2018).

Behavioural problems in childhood can impair the accumulation of human and social

[1]The Centers for Disease Control and Prevention (CDC) declares that there is no safe level of lead exposure but has set a BLL $\geqslant 5\mu g/dL$ as the reference level at which children should be monitored.

capital that may continue to affect adult behaviour (Reyes, 2015). Even low levels of lead in blood have been shown to affect academic performance; Aizer and colleagues (2018) find that reducing BLLs of preschool children increases third grade reading and math test scores. Further, school suspensions have been found to be predictive of future criminal activity amongst children with high BLLs (Aizer & Currie, 2017).

Lead increases an individual's propensity to engage in impulsive activity and take greater risks, shifting the distribution of impulsiveness and aggression in a population (Reyes, 2015). Associational studies have found correlations between high pre- and post-natal BLLs and higher rates of arrest, including for offences involving violence (Wright et al., 2008). Further, lead emissions in the air have been linked to higher rates of assault (Taylor et al., 2016). While previous studies are limited in their analysis of causality, some recent research in economics has attempted to overcome the identification problem between lead and crime.

By exploiting leaded water pipes as one source of exogenous variation in lead, Feigenbaum and Muller (2016) show cities that used lead pipes had higher homicide rates in the early 20th century. Further, Reyes (2015) exploits both longitudinal data on birth cohorts born at different times during the leaded gasoline phasedown and variation across U.S. states in the timing of the lead phasedown to predict the effect of lead on a range of adolescent behaviours. She finds that higher lead exposure as a child is predictive of greater behavioural problems in adolescence with higher elasticities found for children who are impulsive, have temper and bullying problems, are pregnant as a teenager and engage in criminal behaviour as juveniles.

Further, Aizer and Currie (2017) instrument an interaction between birth year and proximity of residential address to high traffic roads within a neighbourhood to predict BLLs of pre-school children in Rhode Island. Historically, soil near high traffic roads has been contaminated with more lead than soil further from roads due to greater leaded gasoline emissions. The authors find that high BLLs are predictive of increased suspension from school and higher probability of juvenile incarceration for boys only. Reducing measurement error in lead and improving causal identification of the lead-crime link has been a key focus of recent work in economics in this field.

Chapter 3

Data

In this chapter I describe the data sources used in this thesis. Data used to measure intergenerational mobility is constructed by the team at Opportunity Insights (Chetty et al., 2018). Crime and soil statistics are by Curci and Masera (2019). I combine these two databases as well as collect additional data on crime, demographics and economic variables to create a rich dataset on 302 U.S. city centres.

Chetty et al. (2018a): Opportunity Atlas

Chetty et al. (2018a) construct an anonymised longitudinal micro dataset for all children born in the 1978-83 birth cohorts in the U.S. The 1978-83 birth cohorts are individuals who were between the age of 31 and 36 in 2014-15 when mobility outcome measures were taken, or between 36 and 41 today. The mobility measures compiled by Chetty et al. (2018a) taken when individuals are in their thirties provides an accurate and reliable estimate of lifetime earnings as mobility estimates typically stabilise by the time individuals reach this age and are thus subject to minimal measurement error (Mazumder, 2005).

The authors combine three sources of data from the U.S. Census Bureau: (1) the 2000 and 2010 Decennial Census short forms; (2) federal income tax returns for 1989, 1994, 1995, and 1998-2015; and (3) the 2000 Decennial Census long form and the 2005-2015 American Community Surveys. The resulting publicly available dataset is comprised of data on predicted outcomes, including earnings, incarceration rates and educational attainment, for 20.5 million Americans, or 96% of the target population.

The primary outcome of interest that I use to measure intergenerational mobility is a child's income rank conditional on their parent's income percentile. This mobility outcome measures a child's predicted income rank using individual earnings in 2014-2015, relative to other individuals in the same birth cohort and conditional on their parent's income percentile. This rank-based approach follows previous standards and allows me to estimate relative measures of mobility which is useful in determining the economic success of an individual relative to their peers (Dahl & DeLeire, 2008). Conditional expectations of children's mean ranks given their parents' ranks have also been previously shown to be well approximated by a linear function, providing ease in estimation and interpretation (Chetty et al., 2018b). Further, percentile ranks rather than actual dollar amounts have previously been found to yield more precise and stable estimates (Chetty et al., 2014). Thus, income ranks observed when individuals are in their early to mid-thirties are likely to accurately reflect earnings in later years.

Parents are ranked relative to all other parents with children born in the same year using an average of parental earnings in the years 1995 to 2000, when children are between 12 and 22 years old. Parents' income is constructed at five percentiles: 1st, 25th, 50th, 75th and 100th percentiles, with the 1st percentile corresponding to the poorest 1% of the distribution. If a Census tract does not have data at a specific percentile, Chetty et al. (2018a) predict average outcomes for a child using parental incomes of children of the same race and gender close to the percentile, for instance using the 24th or 26th percentile to predict the 25th percentile.

Individuals are mapped back to the Census tract they grew up in and children are assigned a Census tract proportional to the amount of time spent during childhood. U.S. Census tracts are the smallest geographical unit and consist of 4,200 people on average. The Opportunity Atlas estimates children's outcomes in 70,000 Census tracts. To protect privacy, estimates are not published for a Census tract with 20 or fewer children. Further, a small amount of noise is injected to the estimates of individuals in each tract, however the authors state that this does not affect estimates meaningfully.

Curci and Masera (2019)

Data used to construct my instrument, violent crime, and historical socio-economic and demographic controls are taken from Curci and Masera (2019) who assemble a unique panel database of 325 city centres for years 1960 to 2014. The authors use data from the F.B.I. Uniform Crime Reporting (UCR) Program (U.S. Department of Justice) to measure violent crime rates. I follow Curci and Masera's (2019) methodology and use the F.B.I. definition of violent crime as the sum of murder and non-negligent manslaughter, total robberies, rape and aggravated assaults. I use total violent crime per capita at the U.S. place level as the endogenous variable to be predicted by my instrument.

This data on crime is merged with data from Baum-Snow (2007) for social, economic and demographic characteristics of city centres and Metroplitan Statistical Areas (MSAs), larger units of geography that encapsulate both a city centre and its surrounds. Curci and Masera (2019) use Baum-Snow's (2007) definition of a city centre as the U.S. place with the largest population in 1950, with geography fixed at the 2000 definition. As lead poisoning is expected to affect violent crime rates in areas where there is high population density, I follow Curci and Masera (2019) and focus my analysis on city centres only.

For the construction of my instrument, I use the average soil pH level for every U.S. Census place in my sample. Information about soil pH is taken from the U.S. Geological Survey General Soil Map (U.S. Department of Agriculture). The soil pH measure is 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. National consumption of tetraethyl lead as gasoline additive used for time series analyses comes from the U.S. Bureau of Mines Mineral Yearbooks. I use a binary measure and define good soil as neutral soil pH, between 6.8 and 7.7, and bad soil as soil that is either acidic, with a pH value below 6.8, or alkaline, with soil pH above 7.7. Greater discussion of the relevance of soil pH and lead is outlined in Section 4.1 and discussion of the continuous measure of soil pH is detailed in Section 6.3.

Other Data

Data used for other control variables and variables needed for an analysis of mechanisms in Section 5 have also been collected. Data on education, population demographics and race is sourced from IPUMS National Historical Geographic Information System (NHGIS). Data on crime, policing and arrest rates is taken from the F.B.I. UCR Program (U.S. Department of Justice).

Final Dataset

To create my final dataset I merge the data by Chetty et al. (2018a) and Curci and Masera (2019). I aggregate the tract level outcome data in Chetty et al. (2018a) to the place level by computing average outcomes across all tracts in a Census place. The resulting dataset is at the city centre level with data for 302 cities, with 45 good soil cities and 257 bad soil cities. Mean income ranks for the 302 cities in my dataset are reported in Table 1, across all males and by race. Table 1 shows that child income ranks increase with parent's income percentile, and black male income ranks are below those of whites males at every income percentile. Further, Table 1 also shows mean income ranks for children raised in bad soil cities are always below those of children raised in good soil cities.

While Chetty et al. (2018a) provide estimates for five race and ethnicity categories – Hispanic, White, Black, Asian and American Indian – I focus my analysis on white and black individuals. Limited data on other racial groups in the cities in my sample where population sizes of non-blacks and non-whites are smaller limits a rich analysis of other races. Further, my main analysis focuses specifically on white and black males as previous literature has found the largest and most persistent racial gaps in intergenerational mobility for males. Gender differences in other outcomes including high school dropout, college attendance and incarceration are all also larger for men than for women, which further motivates my primary focus on males. Analysis for white and black females can be found in Appendix A.4.

Table 1: Sample mean income ranks by city and race

	Black + white men			**White men**			**Black men**		
	All (n=549)	GS (n=73)	BS (n=476)	All (n=302)	GS (n=45)	BS (n=257)	All (n=247)	GS (n=28)	BS (n=219)
1st percentile ($2,200)	0.357	0.398	0.350	0.400	0.438	0.393	0.304	0.334	0.300
25th percentile ($27,000)	0.437	0.471	0.432	0.483	0.511	0.478	0.382	0.407	0.378
50th percentile ($55,000)	0.494	0.522	0.489	0.543	0.564	0.540	0.433	0.456	0.430
75th percentile ($94,000)	0.550	0.573	0.546	0.604	0.617	0.602	0.483	0.502	0.480
100th percentile ($1,500,000)	0.654	0.667	0.652	0.702	0.703	0.701	0.596	0.609	0.595

Notes: Numbers reported are sample mean income ranks of children in 2014-15 by parental income percentile, city and race. All: all cities. GS: good soil cities only (pH between 6.8 and 7.7). BS: bad soil cities only (pH below 6.8 or above 7.7). Dollar figures in parentheses next to percentile level correspond to amount of earnings at that percentile measured in 2015 USD.

Furthermore, I compute the total violent crime rate per capita across the years relevant for the children in my sample, that is, after the first child in my sample has been born until when the mobility data is measured (1978-2014). I use total violent crime rates in a city as a measure for a city's historical, or cumulative, violent crime rate by summing a city's violent crime rate across all years from 1978 to 2014. This summarised variable tracks both the historical rise and fall of violent crime rates in the U.S., which allows for a relative comparison of cities' changes in crime trends. I later standardise this variable across all cities in my sample when conducting my main analysis. Summary statistics for total violent crime rates across all cities and by city soil quality are listed in Table 2, with robbery and aggravated assault contributing most to the total violent crime rate. Further, bad soil cities have higher average violent crime rates and a wider variance in crime relative to good soil cities.

Table 2: Summary statistics for violent crime rates by city

	Mean (Std. Dev.)	Min	Max
Panel A: All cities (n=302)			
Total violent crime	302.57 (190.39)	26.90	1263.85
Murder + manslaughter	3.87 (3.16)	0.25	18.49
Rape	19.98 (9.28)	2.22	69.23
Robbery	102.54 (85.52)	6.74	462.07
Aggravated assault	176.17 (115.89)	13.82	977.03
Panel B: Good soil cities (n=45)			
Total violent crime	208.89 (118.04)	46.11	536.97
Murder + manslaughter	2.44 (1.75)	0.37	7.06
Rape	17.07 (5.98)	6.61	30.02
Robbery	55.57 (47.66)	6.74	233.69
Aggravated assault	133.82 (75.41)	31.95	389.71
Panel C: Bad soil cities (n=257)			
Total violent crime	318.97 (195.99)	26.90	1263.85
Murder + manslaughter	4.12 (3.28)	0.25	18.49
Rape	20.49 (9.66)	2.22	69.23
Robbery	110.77 (88.05)	7.03	462.07
Aggravated assault	183.59 (120.18)	13.82	977.03

Notes: All rates are the sum across years 1978-2014 per 1,000 people. Violent crimes are offences that involve force or threat of force. Total violent crime: sum of below four categories of violent crime. Murder + manslaughter: murder and non-negligent manslaughter. Rape: including forcible (pre-2013 definition) and attempted rape. Robbery: all robberies including those with weapon. Aggravated assault: assault with intent to inflict injury, usually with weapon. Good soil cities: pH between 6.8 and 7.7. Bad soil cities: pH below 6.8 or above 7.7.

Chapter 4

Reduced Form Specification

In this chapter I first present a conceptual background motivating the relevance of lead and soil pH. Next I discuss the identification assumptions required for a reduced form model. Specifically, I motivate the relevance of lead and violent crime using time series analysis, first stage and event study regressions. I then discuss the exogeneity assumption and present balance of covariates tests that provide evidence against differential pre-treatment trends across cities, allowing me to conclude that soil pH is as good as randomly assigned. Next I set-up my reduced form model and discuss the results of this estimation, finding strong effects that are heterogeneous by race. In the final section of this chapter I present evidence of lead's effect on other neighbourhood outcomes as evidence for neighbourhood decay, motivating the exclusion restriction discussed in Chapter 5.

4.1 Conceptual background: Lead and soil

Human exposure to lead can occur through inhalation of gasoline emissions in the air or by direct contact with lead contaminated soil. Before its phasedown in 1975, lead was highly concentrated in gasoline as tetraethyl lead additive was widely used. The boom in the transportation industry and increased use of cars following World War II is associated with the rise in consumption of leaded gasoline (Nriagu, 1990). Gasoline emissions by vehicles were absorbed by the soil in the environment. Humans come into contact with the soil via direct hand-to-mouth contact as young children sometimes eat soil (pica). Alternatively, lead contaminated soil and dust can enter homes through open doors and windows, or through shoes and clothing (Hunt, Johnson & Griffith, 2006). Roadside soil resuspension due to industrial, mining or smelting activity can also result in inhalation of residual lead causing lead poisoning (Laidlaw & Filipelli, 2008).

The bioavailability of lead in the environment can be proxied by a standardised geological measure of pH value that predicts human lead exposure. While the small amount of naturally occurring lead in soil is in the deeper or non-bioavailable layers of soil, lead generated by human activity or expelled by cars is deposited onto and retained in surface level soil where lead is highly bioavailable (Laidlaw & Filipelli, 2008). The quality of soil is determined by its pH value. I use Curci and Masera's (2019) binary definition of good soil: a city centre with a surface level soil pH value between 6.8 and 7.7. Soil is closest to neutral and is geologically least likely to absorb lead when its pH is within these values. A city centre with soil pH less than 6.8 (acidic) or greater than 7.7 (alkaline) is thus defined as having bad soil and is expected to transmit lead to humans upon contact. Curci and Masera (2019) use machine learning tools to choose this interval of pH levels that maximises the F-statistic on the excluded instrument. More details on the construction of the instrument can be found in their paper. Further, while my main analysis uses the binary definition of soil pH, I show in Section 6.3 that results are not sensitive to using a continuous definition.

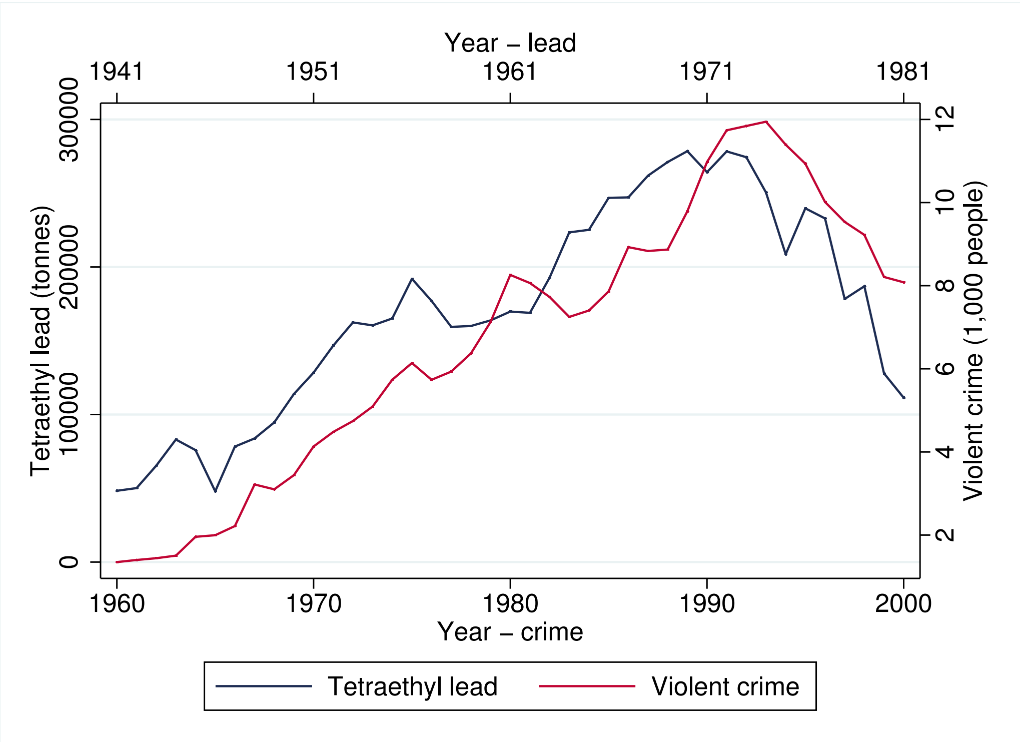
4.2 Relevance

To provide evidence for the relevance assumption required for my reduced form specification, I exploit time variation in national lagged lead consumption, proxied by lead as gasoline additive in tonnes, and cross-sectional variation in soil pH levels across city centres. The U.S. experienced a surge in violent crime between the 1960s and 1990s. In 1960, the average violent crime rate across U.S. cities in my sample was 1.3 crimes per 1,000 people, while at the peak of crime in 1991 U.S. city centres had an average rate of 11.7 violent crimes per 1,000 people. Further, national consumption of tetraethyl lead as gasoline additive peaked in 1972 at 278,340 tonnes, almost six times higher than consumption in 1941. I exploit the relationship between this dramatic rise in violent crime and the preceding surge in lead consumption, which can be observed in the time series analysis in Figure 1.

An age-crime relationship is observed in Figure 1 where the violent crime peak in 1991-92 occurs 19 years after the peak in lead consumption in 1971-72. Comparing this peak in violent crime with the peak in lead consumption suggests that the lead-crime relationship occurs with a lag of about 19 years. This age structure observed in the lead-crime relationship is supported by developmental criminological literature that indicates the peak of criminal propensity typically occurs during late teenage years, around 18 or 19 years old (Hirschi & Gottfredson, 1983; Farrington, 1986). Lead poisoned children are thus expected to have the highest potential for delinquency at age 19 (Taylor et al., 2016; Nevin, 2007). Further, the children in my sample were born between 1978 and 1983, just after the peak in national lead consumption, and so are expected to have a high probability of exposure. Moreover, 88% of children aged 1 to 5 years old in the 1976-1980 National Health and Nutrition Examination Survey had a BLL greater than 10ug/dL which further indicates the children in my sample were likely exposed to lead at some level during their early childhood years (Dapul & Laraque, 2014).

Further, Figure 2 allows us to compare how cities with good and bad soil were differentially affected by the same national time trends in leaded gasoline consumption. I exploit differential trends in violent crime due to different levels of lead exposure across U.S. cities in a setting similar to a Difference-in-Difference (DiD), where a city with bad soil represents an intention to be treated with high violent crime. In 1960, before the rise in lagged tetraethyl lead consumption, violent crime rates between good and bad soil cities appear similar. In fact, the average violent crime rate in 1960 is 1.4 crimes per 1,000 people for bad soil cities and 1.2 crimes per 1,000 people for good soil cities in my sample. The cities' crime rates diverged during the rise in lagged lead consumption as the treatment took effect. While violent crime peaks in all U.S. cities in 1991, cities with bad soil observe higher increases in their crime rates relative to cities with good soil. The crime rate peak in places with bad soil is almost double that of places with good soil, with a violent crime rate of 12.6 crimes per 1,000 residents in 1991.

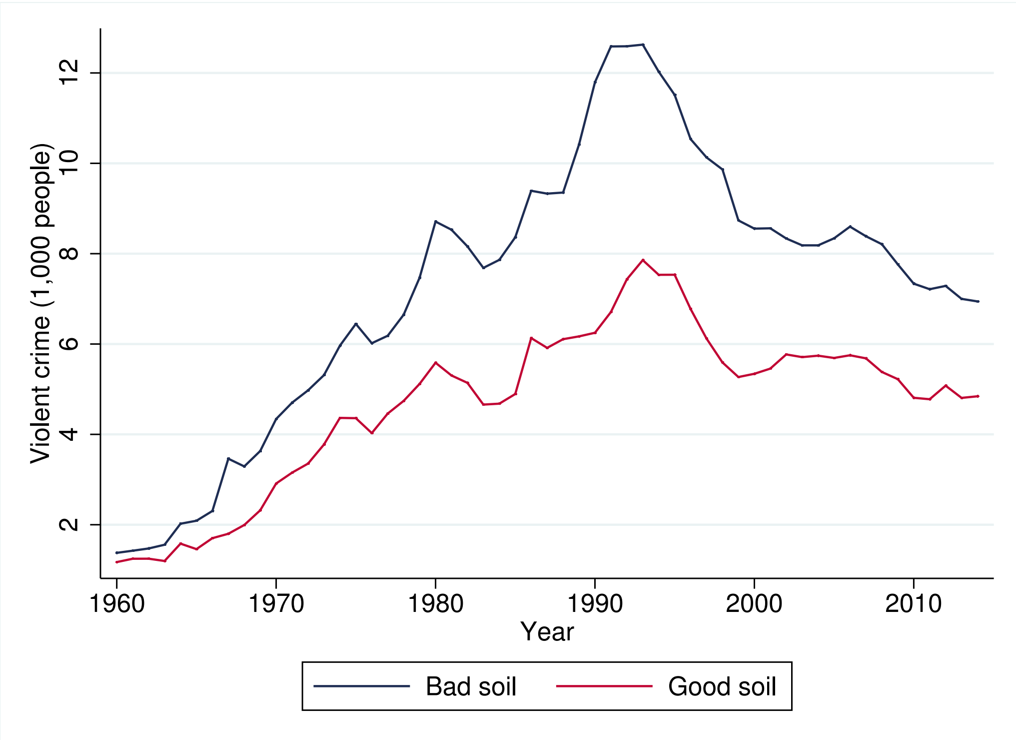
Figure 1: Time series of violent crime rates in city centres and national consumption of tetraethyl lead 19 years prior



Notes: Tetraethyl lead: tonnes of tetraethyl lead consumed in U.S. as gasoline additive lagged by 19 years. Violent crime: total violent crime rate per 1,000 people in city centres.

I argue that this historical shock to violent crime in the U.S. triggered a process of neighbourhood decay in cities with bad soil where the population's susceptibility to crime was higher. The accumulation of high crime in the years leading up to the peak in crime in 1991 encourages the development of poor neighbourhoods. After the prohibition of leaded gasoline when lead consumption decreases, violent crime rates across cities appear similar again. Cities with good and bad soil have little differences in their violent crime rates today; in 2014, cities with bad soil had only 1.2 more crimes per 1,000 residents compared to good soil cities. Even after the shock to violent crime has disappeared, damage to neighbourhood amenities that contribute to the persistence of poor neighbourhoods continue to exist. I argue that it is this development and persistence of poor neighbourhood amenities and public goods that contributes to poor mobility outcomes across generations.

Figure 2: Time series of violent crime rates in city centres by soil quality



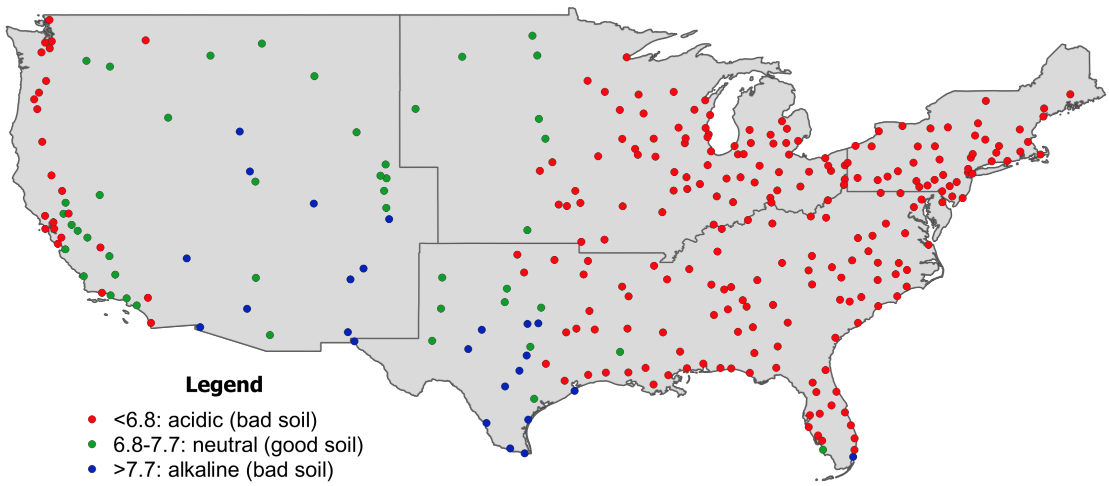
Notes: Bad soil: cities with pH below 6.8 or greater than 7.7. Good soil: cities with pH between 6.8 and 7.7. Violent crime: total violent crime rate per 1,000 people in city centres.

The map in Figure 3 represents the geography of the variation in soil pH levels across city centres in the U.S.. Acidic (bad) soil tends to cluster in the East Coast while soil pH seems to be more evenly distributed across the rest of the country. Given this clustering of bad soil in the East, I control for Census region fixed effects that divides the nation into four regions: West, Midwest, Northeast and South[1].

[1] Census regions are defined by the U.S. Census as: *West*: Pacific (California, Oregon,

After controlling for Census region trends and exploiting variation within regions only, soil pH is as good as randomly assigned. The exogeneity assumption is further discussed in Section 4.3.

Figure 3: Map of soil pH levels in U.S. city centres with region boundaries



Notes: Map reports soil pH levels of all city centres in my sample and the four U.S. Census regions.

The assumption of instrument relevance is satisfied after running a first stage regression of violent crime rates on the good soil dummy, reported in Table 3. Using variation within Census region only, cities with good soil have 108.6 lower incidents of reported violent crime per 1,000 people across all years in my sample (1960-2014) relative to bad soil cities. Restricting the sample to the year the first child was born (1978-2014), good soil significantly predicts lower rates of violent crime with 89.8 lower incidents of reported violent crime per 1,000 people across the 36 years in my sample, or 2.5 per year. Furthermore, the F-statistic increases from 16.68 to 17.07 when analysing the effect of soil pH on crime for years from 1978 only (Column 4). Soil pH thus is a strong predictor of the history of violent crime in a city.

Event study results reported in Table 4 also estimate the effect of the good soil dummy on violent crime in different years and provide further support for the relevance of my instrument. As expected, soil pH does not affect violent crime rates

Washington) and Mountain (Arizona, Colorado, Idaho, New Mexico, Montana, Utah, Nevada, Wyoming); *Midwest*: West North Central (Iowa, Nebraska, Kansas, North Dakota, Minnesota, South Dakota, Missouri) and East North Central (Indiana, Illinois, Michigan, Ohio, Wisconsin); *Northeast*: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont) and Middle Atlantic (New Jersey, New York, Pennsylvania); *South*: West South Central (Arkansas, Louisiana, Oklahoma, Texas), East South Central (Alabama, Kentucky, Mississippi, Tennessee), and South Atlantic (Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia).

in 1960, supporting the argument for parallel pre-treatment trends in crime that is required of a DiD model. Further, good soil has the largest effect on crime in 1990, a decrease of 4.3 crimes per 1,000 people relative to bad soil cities, corresponding to the historical peak in violent crime in the U.S. when my instrument is expected to be the most relevant. The F-statistic is also higher in 1990 relative to other years, suggesting soil pH explains more of the variation in violent crime when cities' crime rates diverge and when national crime rates are close to the historic peak, supporting the relevance of soil pH and crime.

Table 3: Effect of soil pH on violent crime in city centres

	(1)	(2)	(3)	(4)
	Violent crime	Violent crime	Violent crime	Violent crime
Good soil	-0.1340***	-0.1139***	-0.1086***	-0.0898***
	(0.0263)	(0.0214)	(0.0266)	(0.0217)
Constant	0.3897***	0.3236***	0.3859***	0.3200***
	(0.0152)	(0.0124)	(0.0147)	(0.0120)
Observations	302	302	302	302
R^2	0.041	0.045	0.065	0.073
Adjusted R^2	0.038	0.041	0.052	0.060
F	25.988	28.299	16.681	17.070
Year	1960-2014	1978-2014	1960-2014	1978-2014
C. region FE	No	No	Yes	Yes

Notes: Violent crime: sum of violent crime per capita in city centre across years indicated. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

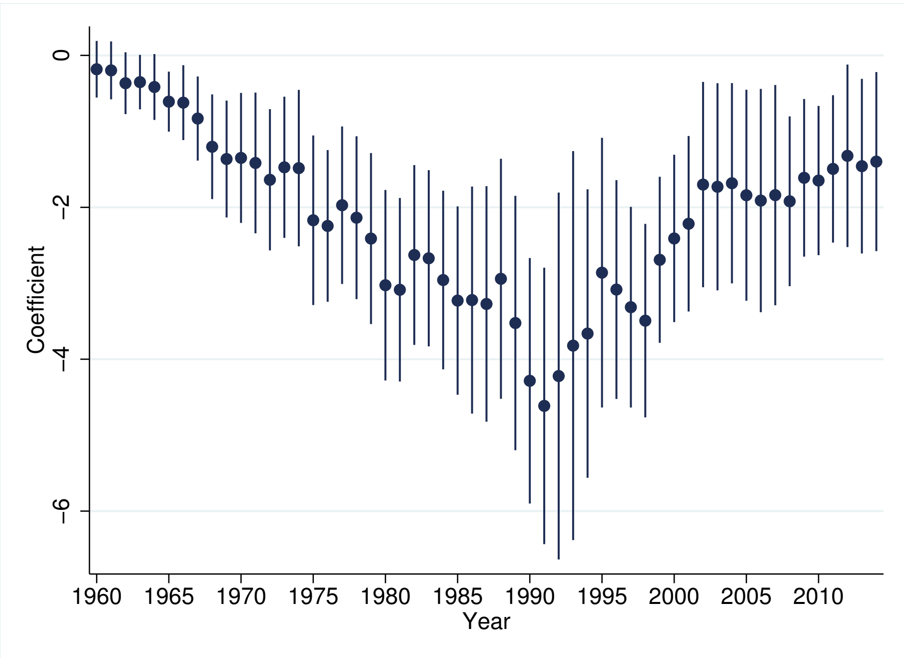
Furthermore, I run a more comprehensive event study for the full set of years in my sample (1960-2014) to ascertain the effect of soil pH on violent crime rates in different years across good and bad soil cities. Figure 4 plots the results of this regression, which is reported in Table 20 in Appendix A.2. This event study supports the time series analysis discussed in this section, where good and bad soil cities do not have significant differences in their violent crime rates prior to the rise in lead consumption, providing support for parallel trends. Specifically, cities do not experience significant differences in their violent crime rates until 1965, when good soil begins to significantly predict lower violent crime. Figure 4 confirms soil pH is most predictive of differences in violent crime rates across cities in 1991, with these differences decreasing but remaining significant over time, suggesting soil pH has lasting effects on crime long after the regulation of lead. Thus, these event study results provide further evidence of the relevance of my instrument.

Table 4: Effect of soil pH on violent crime in city centres in different years

	(1)	(2)	(3)	(4)	(5)	(6)
	Violent crime	Violent crime	Violent crime	Violent crime	Violent crime	Violent crime
Good soil	-0.1819	-1.3496**	-3.0259***	-4.2840***	-2.4100***	-1.6477**
	(0.1902)	(0.4367)	(0.6398)	(0.8245)	(0.5621)	(0.5013)
Constant	1.4002***	4.4134***	8.8456***	11.7470***	8.5011***	7.2470***
	(0.0852)	(0.2441)	(0.4298)	(0.5408)	(0.3249)	(0.2551)
Observations	289	294	299	295	287	297
R^2	0.079	0.028	0.052	0.081	0.109	0.076
Adjusted R^2	0.066	0.015	0.039	0.069	0.096	0.063
F	0.915	9.553	22.369	26.996	18.382	10.802
Year	1960	1970	1980	1990	2000	2010
C. region FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Violent crime: violent crime per 1,000 people in city centre in year indicated. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4: Event study results: Effect of good soil on violent crime



Notes: Graph plots coefficients and 95% confidence intervals of event study regression reported in Table 20. Coefficients obtained regressing violent crime per 1,000 people in city centre on year dummies equal to 1 if year is as indicated and good soil equals 1, controlling for Census region times year fixed effects and using standard errors clustered on city-year. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7.

4.3 Exogeneity

The fundamental identifying assumption required for my reduced form model is that soil pH is randomly assigned across city centres in the U.S.. That is, soil pH is random and independent of the potential factors that may affect intergenerational mobility. While I can check whether good and bad soil cities have parallel pre-treatment trends in crime rates, I am unable to check whether cities are significantly different in their intergenerational mobility outcomes prior to the treatment as I do not have data on intergenerational mobility before the rise in crime. However, if places with good and bad soil have similar pre-treatment trends in other observable characteristics, this may be an indication that mobility outcomes were also similar prior to the shock in crime.

American cities do not have significant differences in their violent crime rates before treatment start, as observed in Figure 2 and confirmed by Column 1 of Table 4 in the previous section. The event study results discussed above (Figure 4 and Table 20 in Appendix A.2) also confirm U.S. cities did not experience different violent crime rates until 1965. Table 5 below also shows that after controlling for region fixed effects, cities do not differ in any of their 1960 crime rates. The need for region fixed effects to control for potential endogeneity of soil pH was discussed in Section 4.2. Therefore, using variation in soil pH within regions only ensures soil pH is as good as randomly assigned and that cities are balanced in their crime rates.

Moreover, city centres do not have significant differences in most of their pre-treatment observable characteristics, after controlling for region specific trends. I conduct a balance of covariates analysis, reported in Table 21 in Appendix A.3, to compare cities' observable characteristics by soil quality. Table 21 reports this test of balanced levels for variables at both the city centre and MSA level, which includes both the city centre and the suburbs. It is important to note that my main analysis is conducted at the city centre level, and that only two variables exhibit unbalanced levels in their city centre values: percentage of the population black and percentage of housing occupied with an automobile. Table 22 in Appendix A.3 shows that my reduced form results are robust to the inclusion of these two unbalanced variables, with coefficient magnitude and significance decreasing only slightly.

The balancing test of trends also reported in Table 21 shows that after controlling for region specific fixed effects, cities with good and bad soil do not have different trends in any of the demographic and social characteristics that may affect mobility, except for one variable: percentage of population 5 years old or younger. The positive coefficient here indicates that good soil cities experienced a positive trend in their young population between 1950 and 1960, however the direction of the bias that may affect mobility is unclear. Nevertheless, I show in Table 23 in Appendix A.3 that my main results are robust to the inclusion of this variable as a control, with predicted effects in the same direction as my reduced form model. Greater discussion of balancing tests is presented in Appendix A.3.

Table 5: Balancing test of pre-treatment crime rates

	(1) Mean	(2) All cities	(3) Inside region
Violent crime CC	1.47	-.21	-.18
Murder CC	.05	-.01	-.002
Manslaughter CC	.04	-.001	-.007
Rape CC	.07	.005	-.003
Robbery CC	.50	.04	-.06
Assault CC	.84	-.25*	-.12
Burglary CC	6.14	.55	-.11
Larceny CC	16.94	7.80***	2.40
Vehicle theft CC	2.42	.27	-.18

Notes: Mean: mean value of variable in 1960. All cities: coefficient obtained regressing variable on good soil dummy. Inside region: coefficient obtained regressing variable on good soil dummy controlling for Census region fixed effects. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. CC: city centre. Year of data: 1960. All rates are per 1,000 people. Standard errors clustered on city have been used. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.4 Monotonicity

The monotonicity assumption requires that lead affects crime in the same direction for all people such that lead poisoning encourages higher crime. For this assumption to be satisfied we should not observe some cities with bad soil with higher violent crime rates and others with lower violent crime.

Evidence for the monotonicity assumption comes from the lead literature which states that lead exposure produces neurological and behavioural deficits that are associated with anti-social and offending patterns (Mason, Harp & Han, 2014). Given the medical literature supports lead having strong negative effects on behaviour, it is highly unlikely that lead exposure will lead to a desistance from crime thus suggesting the monotonicity assumption is satisfied.

4.5 Reduced form model

$$IM_{cc} = E(rank^c_{cc} \mid perct^p_{cc}) = \alpha_0 + \alpha_1(6.8 \leq pH_{cc} \leq 7.7) + \tau_r + \varepsilon_{cc} \quad (4.1)$$

The primary aim of this thesis is to study the effect of neighbourhood decay on intergenerational mobility. Here I model the reduced form model to estimate this relationship and then present the reduced form results as my main results in the next section. Equation 4.1 above estimates the effect of soil quality (pH_{cc}) on intergenerational mobility (IM_{cc}). I use the average expected income rank of children who grow up in a given city ($rank^c_{cc}$) conditional on their parent's income percentile ($perct^p_{cc}$) as my measure for intergenerational mobility.

The reduced form model produces valid estimates of the intention to treat (ITT) effect of neighbourhood decay on mobility when the identification assumption of exogeneity is assumed to hold, as I have shown in Section 4.3. Relevantly, the reduced form results will provide unbiased estimates of ITT effects without requiring satisfaction of the exclusion restriction (Angrist, Imbens & Rubin, 1996). As lead exposure may result in changes to other neighbourhood variables directly, as well as through violent crime, it is difficult to satisfy the exclusion restriction. Reduced form estimations model the true ITT effect of violent crime only if no other neighbourhood level mechanism that affects mobility is directly affected by soil type. I show in Section 4.6.2 that lead does have an effect on other neighbourhood variables, and I later discuss in Chapter 5 the validity of these variables as potential mechanisms mediating the crime-mobility relationship. I also discuss the exclusion restriction required for my IV model in greater detail in Section 5.1.1.

All reduced form regressions exploit the differences between good and bad soil cities that are inside the same U.S. region by controlling for Census region fixed effects and use standard errors clustered at the city level to account for unobserved heterogeneity in the error term.

4.6 Reduced form results

4.6.1 Effect of soil pH on intergenerational mobility

Table 6 Panel A reports the average effect of soil pH on the intergenerational mobility ranks of black and white men. Soil quality has a significant ITT effect on the mobility estimates of children with parents at all income levels excluding the 100th percentile, suggesting high parental income may be a protective factor against the negative effects of lead in a neighbourhood. Children who live in good soil cities have between 2 and 3 percentage points higher income ranks compared to children from families that have the same income but live in bad soil cities. This result confirms Sharkey and Torrats-Espinosa's (2017) finding that a one standard deviation decline in exposure to violent crime during adolescence increases expected income ranks by at least 2 points. Further, I find soil pH has a stronger effect on adult earnings for children who grow up in low income households, which suggests poor children are more susceptible to the harmful effects of lead exposure.

Interestingly, soil pH produces different effects on the mobility of black and white males when analysis is restricted to a within-race sample only (Panel B and C). Growing up in a neighbourhood with good soil significantly increases the mobility ranks of black men only at the 25th and 50th percentiles, relative to other black men with the same family income. The within-black model suggests that black males, when compared with each other, have similar labour market experiences across U.S. cities, indicating that race is a strong predictor of income for black men regardless of a city's exposure to lead.

For white men, soil pH is predictive of earnings at all income percentiles. Growing up in a good soil city significantly increases the mobility ranks of all white men, relative to their same-race peers. Further, the effect of lead is strongest for poorer whites, where white boys raised at the 1st percentile experience an increase in mobility ranks by almost 4 percentage points if they live in good soil cities. This result indicating the gap in mobility across cities is the smallest for the richest 1% suggests rich, white males are relatively protected from poor soil quality and high lead exposure in a city. The differences in mobility estimates between adjacent mobility groups across Panels A and B in Table 6 are statistically significant from zero at the 0.1% level, while only Columns (2) and (3) are significantly different in Panel C. These results are reported in Table 25 in Appendix A.5.

Further, graphs in Appendix A.7 provide visual interpretation of the reduced form results reported in Table 6. In Figure 9 I plot the coefficients and confidence intervals on the good soil dummy, while in Figure 10 I graph the predicted effect of good soil on intergenerational mobility by race sample.

Table 6: Effect of lead on intergenerational mobility, males

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: White and black males					
Good soil	0.0346**	0.0310***	0.0284***	0.0260**	0.0212
	(0.0108)	(0.0078)	(0.0080)	(0.0099)	(0.0166)
Constant	0.3522***	0.4329***	0.4900***	0.5460***	0.6514***
	(0.0024)	(0.0018)	(0.0018)	(0.0022)	(0.0035)
Observations	549	549	549	549	549
R^2	0.077	0.058	0.033	0.015	0.0065
Adjusted R^2	0.070	0.051	0.025	0.008	-0.001
F	10.187	15.775	12.630	6.862	1.616
Panel B: White males					
Good soil	0.0376***	0.0315***	0.0270***	0.0225***	0.0153**
	(0.0081)	(0.0064)	(0.0054)	(0.0048)	(0.0051)
Constant	0.3945***	0.4778***	0.5392***	0.6005***	0.6994***
	(0.0026)	(0.0019)	(0.0016)	(0.0015)	(0.0020)
Observations	302	302	302	302	302
R^2	0.146	0.145	0.144	0.141	0.139
Adjusted R^2	0.134	0.134	0.132	0.130	0.127
F	21.335	24.418	25.292	21.989	8.8470
Panel C: Black males					
Good soil	0.0239	0.0238*	0.0237*	0.0236	0.0234
	(0.0197)	(0.0101)	(0.0119)	(0.0188)	(0.0383)
Constant	0.3010***	0.3788***	0.4306***	0.4803***	0.5936***
	(0.0034)	(0.0020)	(0.0024)	(0.0036)	(0.0069)
Observations	247	247	247	247	247
R^2	0.057	0.115	0.090	0.060	0.039
Adjusted R^2	0.042	0.101	0.075	0.045	0.023
F	1.479	5.519	3.938	1.579	0.374
C. region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Heterogeneous effect of soil pH on intergenerational mobility by race

$$IM_{cc} = E(rank^c_{cc} \mid perct^p_{cc}) = \alpha_0 + \alpha_1(6.8 \leq pH_{cc} \leq 7.7) * Black + \tau_r + \varepsilon_{cc} \quad (4.2)$$

Table 7 reports the heterogeneous reduced form effect of my instrument on mobility by race. Results here estimate Equation 4.2 where I interact the good soil dummy with a race dummy that equals one if race is black. Race alone has a strong effect on mobility and explains on average five times more of the variation in mobility than soil pH. Importantly, black men rank between 9 and 12 percentage points lower in mobility across all parental income percentiles. These large and economically meaningful reduced form effects suggest that race in itself is a strong predictor of intergenerational mobility.

Further, Figure 5, which graphs the results of Table 7, clearly shows a large racial gap in mobility: earnings of white men are above those of black men at all income levels. Results here indicate the racial gap in intergenerational mobility is between 20% and 40% higher in good soil neighbourhoods, which suggests white men who are raised in cities with low rates of decay disproportionately benefit from good city amenities relative to black men living in the same city. This is in line with findings by Chetty et al. (2018b), who state that the intergenerational racial gap in mobility would fall by at most 25% if black and white boys grow up in the same neighbourhoods.

Moreover, I find the racial gap in mobility is most pronounced for the very poor, reaching almost 40% for children raised at the 1st percentile. This result suggests poor, white men benefit more from low rates of neighbourhood decay in a city relative to poor, black men. In other words, mobility outcomes of low income white children are most sensitive to lead and associated neighbourhood problems. Low rates of neighbourhood decay thus appear to amplify existing differences in income mobility between blacks and whites, as the intergenerational racial gap in mobility is wider in areas with good soil.

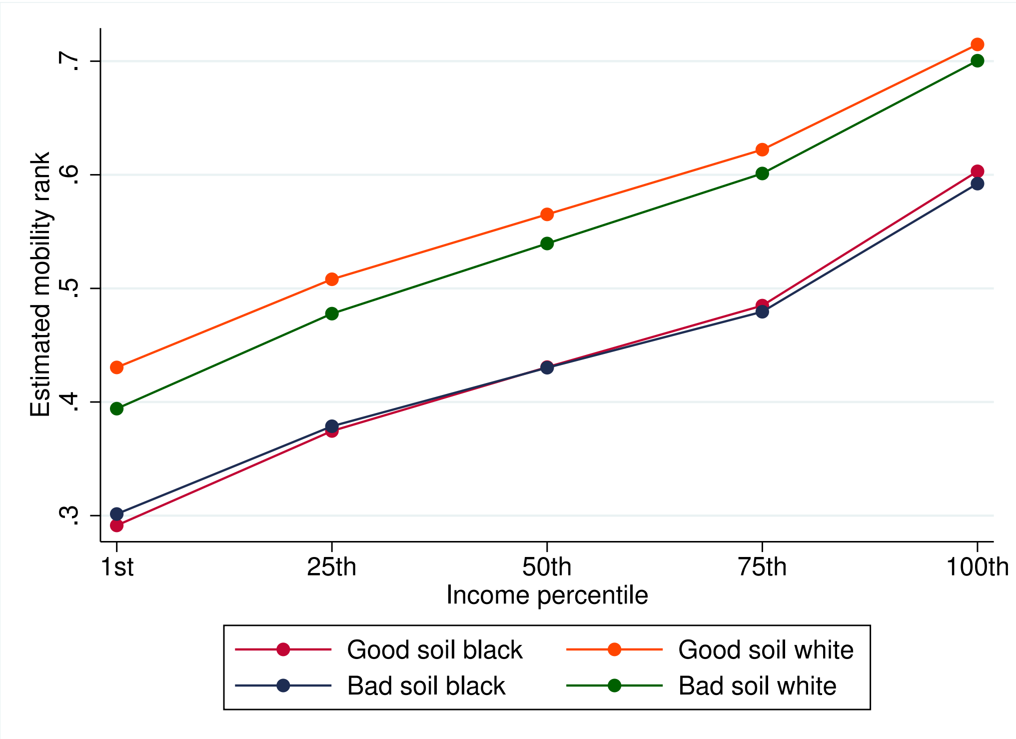
These reduced form findings thus highlight both the power of race and neighbourhoods in shaping long run mobility outcomes. While black men in general have poor upward mobility, white men who grow up in poor neighbourhoods are most susceptible to decaying neighbourhood amenities. Racial gaps in mobility are also smaller in decaying cities as mobility outcomes of white men are closer to black men. In the next section I aim to understand what properties of a neighbourhood may be contributing to this decay.

Table 7: Heterogeneous effect of lead on intergenerational mobility by race, males

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
Good soil=1	0.0363***	0.0302***	0.0256***	0.0209***	0.0143
	(0.0086)	(0.0065)	(0.0056)	(0.0055)	(0.0075)
Black=1	-0.0927***	-0.0991***	-0.1093***	-0.1217***	-0.1082***
	(0.0036)	(0.0024)	(0.0028)	(0.0038)	(0.0069)
Good soil=1 × Black=1	-0.0101	-0.0042	0.0005	0.0054	0.0108
	(0.0198)	(0.0093)	(0.0121)	(0.0200)	(0.0413)
Constant	0.3941***	0.4778***	0.5395***	0.6012***	0.7005***
	(0.0026)	(0.0020)	(0.0017)	(0.0017)	(0.0023)
Observations	549	549	549	549	549
R^2	0.524	0.716	0.723	0.643	0.301
Adjusted R^2	0.519	0.713	0.720	0.639	0.294
F	227.544	606.388	561.209	356.806	83.861
C. region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. Black: dummy equals 1 if race is black and 0 if white. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5: Reduced form results: Effect of soil pH on intergenerational mobility by race



Notes: Graph plots estimated average mobility outcomes by race and city soil quality, as reported in Table 7.

4.6.2 Effect of soil pH on neighbourhood outcomes

$$X_{cc,t} = \nu_0 + \lambda_1(6.8 \leq pH_{cc} \leq 7.7) * Lead_{t-19} + \tau_{r,t} + \epsilon_{cc,t} \tag{4.3}$$

In this section I test whether a city's soil type has an effect on other post-treatment outcomes. If soil pH has an effect on other neighbourhood-level variables, this will provide evidence in favour of a process of neighbourhood decay and will inform the relevance of my instrument. Further, variables that are significantly affected by soil pH may be potential mechanisms mediating the relationship between violent crime and intergenerational mobility. A full discussion of mechanisms is detailed in Section 5.2.

I estimate Equation 4.3 above by regressing an outcome at the city centre level in each year ($X_{cc,t}$) on the good soil dummy variable (pH_{cc}) interacted by tetraethyl lead consumption in gasoline lagged by 19 years ($Lead_{t-19}$), controlling for region specific year trends ($\tau_{r,t}$). I choose outcomes that are indicators of neighbourhood quality and may best represent a process of neighbourhood decay in a city (Aliprantis, Carrol & Young, 2019). I also select variables that may potentially be mediating the lead-mobility channel, that is, are either potentially affected by lead or may be influencing mobility.

Table 8 reports results of this analysis of lead's impact on neighbourhood outcomes. Lead exposure in a city significantly affects the share of black and white residents living in a city centre, suburbanisation, police officers employed and assaulted, incarceration rates, violent and drug crime arrests, high school completion, property values and rates of married couples in a city. Lead does not however have a strong effect on disorder arrest rates, college educational attainment or unemployment rates.

Low exposure to lead decreases the share of blacks living in the city centre by 11 percentage points and increases the share of whites by 10 percentage points across the period 1960 to 2005. Good soil cities also have an 8 percentage point higher share of residents living in the city centre, indicating lower rates of suburbanisation relative to bad soil cities. Thus, more white and less black people tend to remain in a city centre when there is low levels of lead. This result suggests lower rates of racial segregation in good neighbourhoods. In Section 5.2.1 I show that racial segregation in suburbanised neighbourhoods is the strongest mediator of the lead-mobility relationship.

Low lead significantly decreases all crime and policing related variables except for arrests for disorderly conduct, perhaps because they are more widespread or common across all cities. The number of police officers employed and assaulted, incarceration rates, and arrests for both violent and drug crimes are all lower by between 0.32 and 0.40 standard deviations from the mean in good soil cities. The sample means for these and other neighbourhood outcomes are reported in Table 26 in Appendix A.6. This result provides evidence in favour of my main hypothesis: good neighbourhoods are characterised by low crime. I show in Section 5.2.2 that incarceration and arrest rates for violent crime are the two strongest crime related variables mediating the lead-mobility relationship.

Furthermore, educational attainment up to the high school level is significantly higher in cities with low lead, with high school completion rates increasing by 2.88 percentage points to 62.93% of the population in good soil cities. Attainment of a four year college degree is not however significantly different across U.S. cities. Moreover, house values are lower in good soil cities which may be partly due to greater demand induced by higher city centre populations. Further, while unemployment rates are not affected by lead, the number of people married in a city is 32.51% higher in good soil cities across the period 1960 to 2005, suggestive of greater family stability in good quality neighbourhoods. However, I show in Section 5.2.3 and 5.2.4 that high school education, property values and marriage rates are not strong mediators influencing the lead to mobility channel.

Table 8: Effect of lead on neighbourhood outcomes

	Share black	Share white	Population CC	Officers employed	Officers assaulted	Incarceration	Violent arrests
Good soil x lead	-0.1148***	0.0964***	0.8322***	-0.3413***	-0.3572***	-0.3966***	-0.3169***
	(0.0136)	(0.0168)	(0.0590)	(0.0212)	(0.0337)	(0.0278)	(0.0348)
Constant	0.1860***	0.7616***	0.9242***	0.0322***	0.0367***	0.0369***	0.0338**
	(0.0046)	(0.0089)	(0.0154)	(0.0300)	(0.0094)	(0.0108)	(0.0138)
Observations	1204	1204	13851	13759	9600	12899	9600
R^2	0.269	0.252	0.037	0.055	0.037	0.060	0.058
Adjusted R^2	0.260	0.242	0.025	0.042	0.024	0.047	0.045
F	70.91	32.96	198.93	258.22	112.06	202.81	83.04
	Disorder arrests	Drug arrests	High school	College	House value	Unemployment	Married
Good soil x lead	-0.0847	-0.3832***	2.8819**	0.0293	-0.1190*	-0.2114	-0.3251**
	(0.0541)	(0.0372)	(1.0337)	(0.7222)	(0.0497)	(0.2986)	(0.1239)
Constant	0.0101	0.0410***	60.0512***	15.9050***	11.3074***	5.5998***	10.5779***
	(0.0138)	(0.0119)	(0.2057)	(0.2097)	(0.0086)	(0.0546)	(0.0321)
Observations	9600	9000	931	698	930	931	1207
R^2	0.055	0.091	0.848	0.369	0.540	0.301	0.027
Adjusted R^2	0.042	0.079	0.845	0.358	0.532	0.289	0.014
F	2.45	106.16	7.77	0.002	5.74	0.50	6.89
C.region x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Share black: fraction of residents in city of black race. Share white: fraction of residents in city of white race. Population CC: share of population living in city centre relative to suburbs. Officers employed: police officers employed per 1,000 people, deviations from mean. Officers assaulted: police officers assaulted per 1,000 people, deviations from mean. Incarceration: violent crime offences cleared per 1,000 people, deviations from mean. Violent arrests: violent crime arrests per 1,000 people, deviations from mean. Disorder arrests: sum of drunkenness, disorder conduct, driving under influence, curfew loiter, vagrancy and vandalism arrests per 1,000 people, deviations from mean. Drug arrests: sum of drug sale and possession arrests per 1,000 people, deviations from mean. High school: share of those 25 or older with high school diploma. College: share of those 25 or older with 4 year college degree. House value: log median single family house value in city. Unemployment rate: in city. Married: log of population that is married. Good soil x lead: dummy equals 1 if pH in the city centre is between 6.8 and 7.7 multiplied by tonnes of national tetraethyl lead used as gasoline additive 19 years prior, normalised by the maximum level. C.region x year FE: Census region times year fixed effects. Period considered: annual observations from 1960 to 2005. Standard errors clustered on city-year in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 5

Instrumental Variable Specification and Mechanisms

In this chapter I explore potential mechanisms that may be mediating the effect of lead poisoning on intergenerational mobility. The existence of one or more variables mediating the causal channel of lead to mobility may provide evidence of a process of neighbourhood decay and help to satisfy the exclusion restriction required for my IV specification in Section 5.1.

I argue and show that the primary causal mechanism mediating the effect of lead on intergenerational mobility is violent crime. I first discuss the exclusion restriction and stress the need for careful interpretation here before modelling the IV specification. Next I discuss violent crime as a causal mechanism using my IV specification and then move onto a discussion of other potential mechanisms, where I find racial segregation in suburbanised neighbourhoods, and high incarceration and arrest rates to be the strongest non-causal mediators. These mediators appear to be sub-mechanisms of crime as their effect on mobility is most likely triggered by a rise in violent crime. Finally, a discussion and summary of mechanisms is presented in the final section of this chapter.

5.1 Violent crime: Instrumental variable specification

5.1.1 Exclusion restriction

A naive reading of the IV specification detailed in this chapter would assume that my instrument of soil pH only affects intergenerational mobility through violent crime and not any other variable that may influence mobility. This exclusion restriction implies that 19 years after the lead poisoning shock the only thing that has changed between places with good and bad soil that can potentially affect mobility are violent crime rates. However, the exclusion restriction for my IV framework requires lead influence intergenerational mobility through both the direct effect of violent crime and through a process of neighbourhood decay. Since crime causes other neighbourhood-level variables to change, crime may influence intergenerational mobility through these other changes in a neighbourhood. My instrument of soil pH will then only affect individual mobility outcomes through both the direct effect of crime and the indirect effect of crime through other neighbourhood amenities. A complete discussion of mechanisms that allow the exclusion restriction to be satisfied is presented in this chapter.

5.1.2 Instrumental variable model

The main objective of this thesis is to study the effect of neighbourhood decay on intergenerational mobility. In particular, I study the effect of a history of violent crime in a city centre (VC_{cc}) on intergenerational mobility (IM_{cc}) of residents in that city. I argue and show that a history of violent crime is the primary driver of neighbourhood decay in a city. All IV models use U.S. region fixed effects (τ_r) to control for potential endogeneity in my instrument and cluster standard errors at the city level.

$$IM_{cc} = E(rank_{cc}^{c} \mid perct_{cc}^{p}) = \beta_0 + \beta_1 VC_{cc} + \tau_r + \epsilon_{cc} \tag{5.1}$$

$$VC_{cc} = \gamma_0 + \gamma_1(6.8 \leq pH_{cc} \leq 7.7) + \tau_r + \mu_{cc} \tag{5.2}$$

The Ordinary Least Squares (OLS) estimation of the coefficient on the effect of violent crime on intergenerational mobility (β_1) in Equation 5.1, reported in Table 19 in Appendix A.1, may be biased due to reverse causality or omitted variable bias. Cities with lower intergenerational mobility may have poorer amenities which in turn can increase crime rates in the city centre. Omitted unobservable variables correlated to both violent crime and intergenerational mobility can further induce bias in the OLS estimates if unobservables are jointly determining crime and mobility. To solve these identification problems, I use cross-sectional variation in soil pH levels as an instrument for lead exposure that exogenously predicts violent crime at the city centre level.

To the best of my understanding, soil pH has been used as an instrument for violent crime only once before by Curci and Masera (2019). Equation 5.2 estimates the first stage effect of the good soil dummy on violent crime rates in a city centre. Results of this first stage soil-crime relationship were discussed earlier in Section 4.2. In the next section I model Equation 5.1 using soil pH as an IV for violent crime.

5.1.3 Instrumental variable results: Effect of violent crime on intergenerational mobility

The IV regression results reported in Table 9 estimate the effect of violent crime, instrumented by soil pH, on intergenerational mobility in a city. These results estimate the local average treatment effect for the compliers, that is, cities that are induced to have high violent crime due to their bad soil status (Angrist, Imbens & Rubin, 1996).

Panel A shows that violent crime has a significant and negative effect on the intergenerational mobility ranks of men, except for those with parents at the 100th income percentile. IV results presented here confirm the reduced form results in Section 4.5 which find intended exposure to high crime during childhood is predictive of lower intergenerational earnings of children born into poorer households. An increase in violent crime by one standard deviation across years 1978 to 2014 decreases average intergenerational mobility ranks by between 5 and 7 percentage points across all income levels, except for the very rich. Growing up in a city with a history of high violent crime reduces income mobility estimates of all men. However, the effect on the mobility of poorer males is the most pronounced, with children at the 1st and 25th percentile born into high crime cities expected to experience about 7 percentage points lower mobility ranks in response to a one standard deviation increase in crime. Therefore, the elasticity of intergenerational mobility in response to a crime shock is highest for poorer children.

Restricting the sample to black race (Panel C), violent crime only significantly affects the mobility ranks of black children with parents at the 25th income percentile. Growing up in a high crime neighbourhood does not affect black male earnings in comparison to their black peers at any other income level. Further, the soil pH instrument is weak for the black sample, with a low F-statistic. In contrast, high violent crime significantly affects income mobility of white males at all household incomes (Panel B). These results suggest the mobility outcomes of white children are particularly responsive to crime and associated problems in American neighbourhoods. Furthermore, there is heterogeneity in responses of mobility even within a white sample, with mobility ranks of poor, white men most sensitive to violent crime in a city. Violent crime decreases average mobility ranks of white men at the 1st percentile by almost 8 percentage points, while only decreasing by 3 percentage points for those at the 100th percentile. Intergenerational mobility outcomes of very poor, white men are thus the most elastic to violent crime shocks.

$$IM_{cc} = E(rank^c_{cc} \mid perct^p_{cc}) = \beta_0 + \beta_1 VC_{cc} + \tau_r + \tau_b + \epsilon_{cc} \tag{5.3}$$

Table 10 reports the IV results with a race fixed effect to estimate the racial earnings gap. If there is equality of earnings between racial groups, we should expect a zero effect on the coefficient of the race indicator (τ_b) in Equation 5.3 above. Results in Table 10 confirm race alone is a highly significant predictor of mobility at all income levels, suggesting that all black men experience similar inequality in labour market outcomes. In line with reduced form findings presented earlier, black men have mobility ranks between 8 and 11 percentage points lower than their white peers simply because of their race, which highlights existing racial differences in income mobility in the American labour market.

Table 9: Effect of violent crime on intergenerational mobility, males

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: White and black males					
Violent crime	-0.0731**	-0.0655***	-0.0601***	-0.0549*	-0.0447
	(0.0240)	(0.0176)	(0.0177)	(0.0213)	(0.0354)
Observations	549	549	549	549	549
F	9.2461	13.7917	11.5648	6.6490	1.5974
Panel B: White males					
Violent crime	-0.0804***	-0.0674***	-0.0577***	-0.0481***	-0.0326**
	(0.0220)	(0.0176)	(0.0149)	(0.0129)	(0.0121)
Observations	302	302	302	302	302
F	13.334	14.574	14.986	13.888	7.263
Panel C: Black males					
Violent crime	-0.0512	-0.0509*	-0.0507	-0.0505	-0.0501
	(0.0418)	(0.0222)	(0.0266)	(0.0413)	(0.0829)
Observations	247	247	247	247	247
F	1.503	5.268	3.628	1.498	0.365
C. region FE	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Violent crime: sum of violent crime per capita in city centre for years 1978-2014 expressed as deviations from mean, instrumented by good soil dummy. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Effect of violent crime on intergenerational mobility with race indicator, males

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
Violent crime	-0.0689**	-0.0609***	-0.0551**	-0.0492*	-0.0397
	(0.0239)	(0.0171)	(0.0170)	(0.0206)	(0.0354)
Black=1	-0.0830***	-0.0899***	-0.1005***	-0.1132***	-0.1005***
	(0.0064)	(0.0040)	(0.0044)	(0.0062)	(0.0117)
Observations	549	549	549	549	549
F	281.529	730.318	680.282	448.618	109.557
C. region FE	Yes	Yes	Yes	Yes	Yes
Estimation	IV	IV	IV	IV	IV

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Violent crime: sum of violent crime per capita in city centre for years 1978-2014 expressed as deviations from mean, instrumented by good soil dummy. Black: dummy equals 1 if race is black and 0 if white. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Mechanisms and discussion

$$M_{cc} = \phi_0 + \chi_1(6.8 \leq pH_{cc} \leq 7.7) + \tau_r + \epsilon_{cc} \tag{5.4}$$

$$IM_{cc} = \eta_0 + \beta_1 M_{cc} + \beta_2(6.8 \leq pH_{cc} \leq 7.7) + \tau_r + \varepsilon_{cc} \tag{5.5}$$

A mechanism is defined as a variable that mediates the influence of a treatment on an outcome. This will occur when the treatment has an indirect effect on the outcome through the mechanism (Keele, Tingley & Yamamoto, 2015). In this section I test the validity of neighbourhood characteristics as mechanisms. Specifically, I study the neighbourhood outcomes that I show in Section 4.6.2 are significantly affected by lead as potential mechanisms. Namely, I test racial segregation, suburbanisation, incarceration, policing, arrest rates, education, property values and marriage as potential mechanisms mediating the lead-mobility relationship in U.S. neighbourhoods. I find racial segregation, suburbanisation, incarceration and arrest rates are the strongest sub-mechanisms of the lead-mobility pathway, likely triggered by rising violent crime.

In Section 4.6.2, I estimated Equation 5.4 above where I determined which variables are significantly affected by lead exposure. In this section I now estimate Equation 5.5 to determine which variables may serve as non-causal mechanisms affecting intergenerational mobility. I estimate the effect of a potential mechanism on my outcome controlling for my treatment. If both χ_1 and β_1 are significant, then the mediator has a non-causal effect on intergenerational mobility through lead. Any change in the coefficient on soil pH (β_2) from the reduced form estimates in Section 4.6.1 is the estimated mediation effect (MacKinnon et al., 2002).

To interpret this mediation effect as causal, mediator exogeneity conditional on treatment compliance would be required. However, without causal identification, effects of mechanisms detailed in this section can only be interpreted as correlational. Future work can extend on this analysis by exogenously identifying mediator effects.

Table 11: Summary of estimated mediation effects

Variable	*Overall*	*Within whites*	*Within blacks*
Racial segregation	Strong	None	None
Suburbanisation	Strong	Strong	None
Incarceration	Strong	Strong	None
Violent crime arrests	Strong	Strong	None
Policing	Moderate	Weak	Strong
Drug crime arrests	None	None	None
High school education	Weak	Strong	None
Property values	Weak	Moderate	None
Marriage rates	None	Moderate	None

Notes: Overall: pooled white and black race sample. Within whites: white race sample only. Within blacks: black race sample only.

5.2.1 Racial segregation and suburbanisation

Residential segregation across U.S. cities may contribute to racial differences in economic opportunity and access to resources if low quality neighbourhoods also have a high share of residents of minority race. Some literature suggests residential preferences are underpinned by racial sorting into neighbourhoods where households have race-specific preferences over where they live (Aliprantis, Carroll & Young, 2019). This literature finds that at all income levels, the racial gap in neighbourhood quality can be explained by black households living in black neighbourhoods. Other related literature has also studied nation-wide migration patterns such as the Great Migration of blacks from the South to the North as driving residential preferences (Derenoncourt, 2019). Regardless of the driving force, the racial structure of a city can influence income mobility if black Americans tend to live in decaying cities with lower amenity values. I test this potential mechanism by analysing whether the share of blacks living in the city centre is a significant predictor of intergenerational mobility today.

I also analyse whether suburbanisation and the associated white flight phenomenon, the mass movement of white Americans to the suburbs, is a mediating factor of the lead-mobility pathway. The U.S. underwent a period of suburbanisation between the 1960s and 1990s which moved masses of people from the city centres to the suburbs (Baum-Snow, 2007). Previous literature has studied the association between city centre crime rates and suburbanisation (Cullen and Levitt, 1999), and most recently, Curci and Masera (2019) study the causal effect of violent crime on suburbanisation, finding 26 million people left the city centres for the suburbs during the rise of violent crime largely due to a reduction in city centre amenities. Furthermore, only 3.2% of the people who moved to the suburbs were black (Curci & Masera, 2019).

Residential suburbanisation may increase city centre house vacancies, reducing property values and lowering the intergenerational earnings of homeowners. I discuss this potential pathway in Section 5.2.4. Alternatively, the mass movement of people to the suburbs may impact intergenerational mobility if firms' decentralisation results in a movement of businesses to the suburbs. High violent crime and an associated reduction in city centre amenity value may directly result in a firm's decision to relocate to the suburbs to retain their workers, creating new employment centres in the suburbs. The relocation of businesses may reduce job opportunities available to blacks left in the city, maintaining the intergenerational black-white mobility gap if whites are more likely to retain higher income jobs or have greater work choices in the suburbs. As I show in Section 4.6.2, lead does not directly affect unemployment rates, suggesting that relocation decisions of firms causing unemployment of city centre residents is an unlikely pathway mediating the lead-mobility relationship. However, future research could study whether the location decisions of certain industries or types of firms during the suburbanisation era influences intergenerational mobility.

Suburbanisation in the U.S. from the 1960s to 1990s corresponds to the time the children in my sample were growing up and first entering the labour market. Children in my sample were thus more likely to grow up in the suburbs relative to their parents. I test whether a mass movement of people to the suburbs during the rise in violent crime from the 1960s significantly affects income mobility in 2014 by using the share of population living in the city centre relative to the share living in the greater MSA. I also study whether the share of white people living in a city centre is driving mobility to see whether the white flight phenomenon has persistent effects.

I find strong evidence that both racial segregation and suburbanisation are mechanisms mediating the lead-mobility relationship. After controlling for lead exposure with the good soil dummy, increasing the share of blacks living in a city from zero to one decreases mobility ranks of children by between 3 and 4 percentage points (Table 12 Panel A). Interestingly, the effects of racial segregation on mobility are almost completely eliminated in a city that has equal shares of blacks and whites, as increasing the share of whites living in a city from zero to one increases mobility ranks of children by around 3 percentage points after controlling for soil pH (Table 12 Panel B). Furthermore, a city with lower rates of suburbanisation, that is, more residents living in the city centre relative to the suburbs, is expected to have higher intergenerational mobility (Table 12 Panel C).

Residential segregation and suburbanisation in American neighbourhoods explains around 0.2 to 0.5 percentage points of the mobility gap across cities. This is equivalent to explaining between 9% and 14% of the effect of good soil on mobility. Specifically, a higher share of blacks living in the city centre explains around 9% to 11% of the total reduced form effect of good soil on mobility, while the estimated mediation effect for suburbanisation is slightly higher, with a highly urbanised city explaining between 10% and 14% of the total effect of good soil on mobility. Thus, a movement of white people to the suburbs, leaving more black people in the city centre, is expected to decrease intergenerational mobility of residents left in the city centre, partially explaining the effect of bad soil on poor mobility.

Interestingly, when restricting the sample to either whites or blacks, the share of either race in a city does not influence mobility of children compared to their same-race peers (Table 27 Panel A and B in Appendix A.8). This result suggests racial segregation may only affect intergenerational mobility of residents when analysing the differences between the two races. Further, the effect of suburbanisation on mobility is driven by the differences in white male mobility only (Table 27 Panel C in Appendix A.8), providing greater evidence of this white flight phenomenon improving economic outcomes of the white men who remain in the urban centre.

These results confirm previous findings that explain the racial gap in neighbourhood quality in the U.S. as due to black households sorting into black neighbourhoods (Aliprantis, Carrol & Young, 2019). Suburbanisation of cities largely driven by white Americans also contributes to racial segregation of neighbourhoods. My findings suggest that a high share of blacks living in a city may be an indicator of neighbourhood decay. Black Americans forced to remain in the city centre during the suburbanisation era, where amenity value was lower than the suburbs, may have created this gap in neighbourhood quality that is driving a widespread lack of opportunity for blacks and ultimately, poor intergenerational mobility in the long run (Sharkey, 2016). Therefore, racial segregation in highly suburbanised cities is a strong mediator driving the relationship between lead exposure and income mobility. However, given suburbanisation explains differences in white mobility, the few whites who remain in these highly segregated and suburbanised cities may be disproportionately benefiting from existing city amenities, amplifying racial disparities in mobility.

Future work can assess whether differences in education between city centre and suburban residents explains differences in mobility, if higher educated people are more sensitive to crime shocks and migrate to the suburbs in response (Cullen & Levitt, 1999). While I use an average of values covering both the rise and fall of crime in the U.S., further research can also specifically study whether declining crime rates in the U.S. from the early 1990s attracted residential migration back into city centres, reversing the effects of suburbanisation on poor mobility (Ellen & O'Regan, 2010).

Table 12: Mediation test: Racial segregation and suburbanisation

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: Share of blacks living in city centre					
Share black	-0.0423**	-0.0342**	-0.0297*	-0.0259	-0.0101
	(0.0150)	(0.0115)	(0.0117)	(0.0141)	(0.0218)
Good soil	0.0307**	0.0278***	0.0257**	0.0236*	0.0202
	(0.0108)	(0.0077)	(0.0079)	(0.0100)	(0.0169)
Constant	0.3614***	0.4403***	0.4965***	0.5517***	0.6536***
	(0.0046)	(0.0034)	(0.0035)	(0.0044)	(0.0071)
Est. mediation effect	-0.0039	-0.0032	-0.0027	-0.0024	-0.0010
Observations	547	547	547	547	547
Panel B: Share of whites living in city centre					
Share white	0.0275	0.0288*	0.0314**	0.0347*	0.0302
	(0.0150)	(0.0114)	(0.0121)	(0.0150)	(0.0240)
Good soil	0.0326**	0.0289***	0.0261**	0.0234*	0.0189
	(0.0109)	(0.0076)	(0.0079)	(0.0099)	(0.0170)
Constant	0.3329***	0.4127***	0.4681***	0.5219***	0.6304***
	(0.0103)	(0.0078)	(0.0081)	(0.0100)	(0.0158)
Est. mediation effect	-0.0030	-0.0021	-0.0023	-0.0026	-0.0023
Observations	547	547	547	547	547
Panel C: City centre population					
Population CC	0.0066***	0.0054***	0.0046***	0.0037*	0.0023
	(0.0018)	(0.0013)	(0.0013)	(0.0016)	(0.0026)
Good soil	0.0299**	0.0271***	0.0252**	0.0233*	0.0195
	(0.0112)	(0.0081)	(0.0083)	(0.0103)	(0.0173)
Constant	0.3471***	0.4287***	0.4865***	0.5431***	0.6496***
	(0.0028)	(0.0021)	(0.0020)	(0.0024)	(0.0039)
Est. mediation effect	-0.0047	-0.0039	-0.0032	-0.0027	-0.0017
Observations	549	549	549	549	549
C.region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. Share black: fraction of city centre residents of black race, average over years 1980, 1990, 2000 and 2010. Share white: fraction of city centre residents of white race, average over years 1980, 1990, 2000 and 2010. Population CC: share of population living in city centre relative to suburbs, average over annual observations across period 1978 to 2014. Est. mediation effect: estimated change in coefficient on good soil dummy from reduced form results of Table 6 Panel A. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.2 Incarceration and policing

In this section I test whether incarceration, policing and arrest rates are significant mediators of the lead to mobility pathway. High violent crime in a neighbourhood may change the probability of incarceration which in turn can impact future earnings as people are removed from the labour market if they go to jail or prison. Individuals who grow up in a high crime neighbourhood are more likely to become offenders themselves, with those directly exposed to violence more likely to commit violent crimes (Damm & Dustmann, 2014). Further, parental incarceration during a child's critical early years may either directly limit a child's own income mobility due to a lack of parental role model hindering development, or indirectly through increasing their own probability of contact with the legal system (Liu, 2019).

By using neighbourhood incarceration rates across all years the children in my sample are alive (1978-2014), I can test both parental incarceration and a child's own incarceration as potential mechanisms. I use violent crime clearances by arrest rates as a measure of incarceration. Violent crimes that have been cleared, or finalised, most likely result in a sentence of imprisonment due to their severity. Further, I test arrest rates for both violent crimes and drug offences to examine whether high crime cities with high arrest rates following the lead poisoning shock have lower average income mobility.

Results of Table 13 Panel A show that incarceration is a strong mechanism at all income levels, except for at the top 1% of the distribution. Increasing incarceration rates by one standard deviation from the mean across years 1978 to 2014 is associated with a decrease in mobility ranks by between 0.7 and 0.9 percentage points. Furthermore, violent crime arrest rates are also a strong mediator of the lead to mobility channel (Table 13 Panel B). Children at all income levels except for the top 1% have between 0.6 and 0.9 percentage points lower mobility ranks in response to a one standard deviation increase in arrest rates. The estimated mediation effects of incarceration and arrest rates are around 0.1 to 0.3 percentage points of the reduced form effect of good soil found in Section 4.6.1. In other words, violent crime arrests explain 5% to 6% and incarceration explains 8% to 9% of the effect of soil pH on mobility.

Moreover, within-race results suggest that both incarceration and violent crime arrest rates differentiate white male earnings only (Table 27 Panel D and E in Appendix A.8). Black men, in comparison to each other, see no differences in their mobility ranks in response to either high incarceration or arrest rates. This suggests black men's mobility is not responsive to high crime, a result that is similar to the reduced form (Section 4.6.1) and IV findings (Section 5.1.3) which found that neither soil pH nor violent crime differentiates black men's mobility. Further, arrest rates for drug sale or possession are not a mechanism.

I also test policing as a response to the rise in violent crime in U.S. cities as a mechanism for intergenerational mobility by using the number of police officers employed per capita in a given city as a measure for policing. Increased policing in response to high violent crime in a city increases the likelihood of arrest and contact with the justice system and may thus affect intergenerational mobility if particular groups of people or families are repeatedly policed. Alongside mass incarceration of black Americans, the rise in violent crime in the U.S. preceded a rise in policing and increase in number of police officers patrolling the streets (Bacher-Hicks & De la Campa, 2019; Legewie & Fagan, 2019). Whilst greater policing increases the probability of arrest and decreases income earning opportunities, policing may also affect the psychological wellbeing of residents, which in turn may have flow-on effects for job prospects and mobility. Heightened visibility of police may heighten community tensions or fear of crime and could impact the outcomes of law-abiding citizens (Skogan, 1986). Alternatively, greater police officers employed may improve feelings of safety in a community, improving residential outcomes.

Results in Table 13 Panel C show that policing is a strong mechanism for both the very poor and the very rich, but not for middle income earners. Per capita policing rates significantly decrease mobility ranks of children at the 1st and 25th percentile by 0.3 and 0.2 percentage points, respectively. In contrast, policing is associated with an increase in mobility ranks of children at the 100th percentile by 0.3 percentage points. This result suggests high income residents in good neighbourhoods with more visible police officers may feel safer and are protected by a visible police presence, in stark contrast to poorer residents who may feel threatened. Recent research that finds positive spillover effects of policing on white students' educational outcomes, a racial group not likely to interact directly with police, is also in line with this finding (Bacher-Hicks & De la Campa, 2019). Furthermore, the rate of police officers assaulted in a neighbourhood is also a strong mediator, decreasing average mobility ranks by between 0.4 and 0.6 percentage points for children below the 50th percentile (Table 13 Panel D). This result suggests cities with more police officers who are assaulted by civilians, a visible sign of hostility towards police, are negatively associated with poorer mobility outcomes of the poor, an interesting point for future causal analysis.

The results for these two policing related mechanisms together suggest that heightened tensions due to a fear of crime or increased probability of arrest contributes to neighbourhood decay and decreases economic opportunities, particularly for the poor. However, the estimated mediation effects of policing are relatively small, only explaining 0.01 to 0.06 percentage points, or 1% to 2% of the mobility gap across cities. Furthermore, the number of police officers employed may be correlated with greater government expenditure in other areas of the economy that may in turn stimulate greater income mobility, a potential endogeneity issue that should be explored by future research.

Heterogeneity of responses to policing is apparent in the within-race samples of Table 27 Panel D (Appendix A.8). The number of officers employed in a city is a strong mediator of mobility for black men. In fact, policing is the only mechanism that significantly differentiates black men's mobility ranks. Black men living in a city with a strong police force have lower mobility ranks than black men living in neighbourhoods that are not policed. A one standard deviation increase in the per capita rate of police officers employed across years 1978 to 2014 is associated with a 0.2 to 0.9 percentage point decrease in black male mobility. This result may be indicative of racialised policing practices, where black Americans may be disproportionately targeted. This is in line with recent work that finds frequent, unproductive civilian stops by police designed to maintain order increases high school dropout and lowers overall educational performance of black male students in New York City (Bacher-Hicks & De la Campa, 2019; Legewie & Fagan, 2019). Thus, variables detailed in this section together indicate that cities with greater incarceration, higher arrest rates and a stronger police presence have lower intergenerational mobility, an association especially observed amongst low income earners. The divergence of black men's mobility in response to policing is an important point for future causal research.

5.2.3 Educational attainment

Educational outcomes can influence intergenerational mobility if high lead exposure sparks a process of neighbourhood decay that reduces the quality of schools and level of educational attainment in a city, reducing human capital accumulation of residents. High violent crime may result in more young people in a neighbourhood becoming arrested or incarcerated, forcing them to drop out of school or college. Alternatively, high crime neighbourhoods may attract lower public or private investment into schools and educational systems due to a perceived lower rate of return in these neighbourhoods.

I do not find strong evidence that high school completion rates are a mechanism mediating the lead to mobility channel (Table 14). This finding is in line with previous research by Rothstein (2018) who also does not find evidence of school quality driving between-neighbourhood differences in intergenerational mobility. Furthermore, Chetty et al. (2018b) also find that differences in cognitive ability do not explain the persistence of black-white gaps for men.

However, educational attainment up to the high school level appears to be a strong mediator when analysing white male mobility only, suggesting education may differentiate mobility only amongst whites (Table 27 Panel I in Appendix A.8). Future research may study whether these educated men are also the same men who relocated to the suburbs during America's suburbanisation era, further driving racial differences in intergenerational mobility across neighbourhoods.

Table 13: Mediation test: Incarceration, arrests and policing

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: Incarceration for violent crimes					
Incarceration	-0.0087***	-0.0076***	-0.0070***	-0.0066**	-0.0044
	(0.0023)	(0.0017)	(0.0018)	(0.0022)	(0.0037)
Good soil	0.0317**	0.0284***	0.0261***	0.0237*	0.0196
	(0.0107)	(0.0075)	(0.0078)	(0.0099)	(0.0170)
Constant	0.3532***	0.4338***	0.4909***	0.5469***	0.6521***
	(0.0025)	(0.0018)	(0.0019)	(0.0023)	(0.0037)
Est. mediation effect	-0.0029	-0.0026	-0.0023	-0.0023	-0.0016
Observations	545	545	545	545	545
Panel B: Violent crime arrests					
Violent arrests	-0.0094***	-0.0077***	-0.0067***	-0.0058*	-0.0029
	(0.0023)	(0.0016)	(0.0018)	(0.0024)	(0.0041)
Good soil	0.0326**	0.0293***	0.0269***	0.0246*	0.0204
	(0.0107)	(0.0074)	(0.0077)	(0.0098)	(0.0169)
Constant	0.3528***	0.4335***	0.4906***	0.5465***	0.6518***
	(0.0024)	(0.0018)	(0.0019)	(0.0023)	(0.0037)
Est. mediation effect	-0.0020	-0.0017	-0.0015	-0.0014	-0.0008
Observations	545	545	545	545	545
Panel C: Police officers employed					
Officers employed	-0.0033***	-0.0016**	-0.0005	0.0005	0.0030*
	(0.0007)	(0.0005)	(0.0006)	(0.0008)	(0.0013)
Good soil	0.0340**	0.0307***	0.0283***	0.0260**	0.0216
	(0.0109)	(0.0078)	(0.0080)	(0.0099)	(0.0167)
Constant	0.3523***	0.4330***	0.4901***	0.5461***	0.6514***
	(0.0024)	(0.0018)	(0.0018)	(0.0022)	(0.0036)
Est. mediation effect	-0.0006	-0.0003	-0.0001	0.00	0.0004
Observations	545	545	545	545	545
Panel D: Police officers assaulted					
Officers assaulted	-0.0058**	-0.0046**	-0.0038*	-0.0030	-0.0011
	(0.0020)	(0.0015)	(0.0016)	(0.0022)	(0.0037)
Good soil	0.0326**	0.0294***	0.0271***	0.0249*	0.0207
	(0.0108)	(0.0077)	(0.0079)	(0.0100)	(0.0170)
Constant	0.3525***	0.4333***	0.4903***	0.5463***	0.6516***
	(0.0024)	(0.0018)	(0.0019)	(0.0022)	(0.0036)
Est. mediation effect	-0.0020	-0.0016	-0.0013	-0.0011	-0.0005
Observations	545	545	545	545	545
Panel E: Drug crime arrests					
Drug arrests	-0.0035	-0.0020	-0.0009	0.0000	0.0025
	(0.0023)	(0.0018)	(0.0019)	(0.0023)	(0.0036)
Good soil	0.0337**	0.0304***	0.0282***	0.0259**	0.0217
	(0.0109)	(0.0078)	(0.0080)	(0.0100)	(0.0168)
Constant	0.3523***	0.4330***	0.4901***	0.5461***	0.6514***
	(0.0024)	(0.0018)	(0.0019)	(0.0022)	(0.0036)
Est. mediation effect	-0.0009	-0.0006	-0.0002	-0.0001	0.0005
Observations	545	545	545	545	545
C.region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. Incarceration: rate of violent crime offences cleared per 1,000 people, deviations from mean. Violent arrests: rate of violent crime arrests per 1,000 people, deviations from mean. Officers employed: rate of police officers employed per 1,000 people, deviations from mean. Officers assaulted: rate of police officers assaulted per 1,000 people, deviations from mean. Drug arrests: rate of drug crime arrests per 1,000 people, deviations from mean. All variables are averages of annual observations across the period 1978 to 2014. Est. mediation effect: estimated change in coefficient on good soil dummy from reduced form results of Table 6 Panel A. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Mediation test: Educational attainment

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
High school	0.0017*	0.0012*	0.0007	0.0004	-0.0005
	(0.0007)	(0.0005)	(0.0004)	(0.0005)	(0.0010)
Good soil	0.0330**	0.0297***	0.0273**	0.0249*	0.0207
	(0.0117)	(0.0087)	(0.0093)	(0.0116)	(0.0191)
Constant	0.2219***	0.3474***	0.4354***	0.5214***	0.6883***
	(0.0508)	(0.0334)	(0.0317)	(0.0398)	(0.0723)
Est. mediation effect	-0.0016	-0.0013	-0.0011	-0.0011	-0.0005
Observations	433	433	433	433	433
C.region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. High school: share of population with high school diploma, average over years 1980 and 1990. Est. mediation effect: estimated change in coefficient on good soil dummy from reduced form results of Table 6 Panel A. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.4 Property values and family stability

In this section I examine whether property values are associated with intergenerational mobility. Lead exposure may affect mobility through property values if the transmission of wealth across generations has implications for income mobility. Property values are also related to the discussion on suburbanisation of cities in Section 5.2.1. Residential suburbanisation resulting in the movement of people to the suburbs may increase city centre house vacancies, decreasing the value of housing stock in the city centre. High crime in city centres reduces city amenity value and can lead to suburbanisation if disamenities from crime are not fully internalised into property values. A decline in housing stock value can then reduce intergenerational wealth of homeowners.

I find minimal evidence that property values are a mechanism influencing mobility outcomes of residents. However, when estimating this mediation effect for white men only, house values become a significant mediator (Table 27 Panel J in Appendix A.8). Increasing house values by 1% is correlated with increasing white male mobility by between 0.03 and 0.06 percentage points. As whites hold the majority of wealth in the U.S. and are much more likely to own a house than blacks, this result is relatively unsurprising.

Furthermore, I also test whether family stability, estimated using marriage rates in a city, is a significant mediator of the lead-mobility relationship. A reduction in social cohesion or lack of family connection induced by less married couples and more single-headed households in a neighbourhood could be a reflection of poor neighbourhood quality. However, results from Table 15 Panel B indicate that marriage is not a potential mechanism and only affects mobility outcomes of white men relative to each other (Table 27 Panel K in Appendix A.8). Results here and in the previous section together indicate that white men who are educated, own property and are married generally have better labour market outcomes, in comparison to blacks and other whites.

Table 15: Mediation test: House values and marriage

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: Average house value in a city					
House values	0.0403***	0.0224**	0.0095	-0.0034	-0.0254
	(0.0106)	(0.0077)	(0.0086)	(0.0111)	(0.0189)
Good soil	0.0383**	0.0327***	0.0287**	0.0247*	0.0177
	(0.0117)	(0.0090)	(0.0093)	(0.0112)	(0.0178)
Constant	-0.1155	0.1728	0.3804***	0.5856***	0.9477***
	(0.1223)	(0.0894)	(0.0989)	(0.1283)	(0.2181)
Est. mediation effect	0.0037	0.0017	0.0003	-0.0013	-0.0035
Observations	433	433	433	433	433
Panel B: Rates of marriage in a city					
Married	0.0025	0.0009	-0.0005	-0.0020	-0.0031
	(0.0024)	(0.0019)	(0.0018)	(0.0020)	(0.0030)
Good soil	0.0351**	0.0311***	0.0283***	0.0256**	0.0205
	(0.0109)	(0.0078)	(0.0080)	(0.0099)	(0.0165)
Constant	0.3252***	0.4232***	0.4953***	0.5672***	0.6842***
	(0.0262)	(0.0200)	(0.0196)	(0.0225)	(0.0339)
Est. mediation effect	0.0005	0.0001	-0.0001	-0.0004	-0.0007
Observations	549	549	549	549	549
C.region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. House values: log median single family house value, average over years 1980 and 1990. Married: log of population that is married, average over years 1980, 1990 and 2000. Est. mediation effect: estimated change in coefficient on good soil dummy from reduced form results of Table 6 Panel A. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2.5 Summary and discussion of mechanisms

To summarise, high violent crime appears to trigger an increase in incarceration, arrests and policing, leading to the suburbanisation of white Americans and segregation of areas by race in neighbourhoods with the worst intergenerational mobility today. I argue these neighbourhood outcomes are sub-mechanisms of violent crime with changes in these variables triggered most likely by the massive rise in violent crime in the U.S. from the 1960s. While this question of timing of changes would best be answered with a rich panel dataset where mobility is also observed at different times, a point for future research, previous empirical work provides strong evidence that these variables are indeed sub-mechanisms driven by changes in crime.

Literature on racial sorting during the suburbanisation era provides evidence that racial segregation of neighbourhoods was largely due to white Americans abandoning high crime city centres (Curci & Masera, 2019). Literature on mass imprisonment, heightened policing and increased judicial sentencing severity from the 1960s also provide evidence for the sub-mechanisms presented in this chapter as responses to rising crime in the U.S. (Liu, 2019; Bacher-Hicks & De la Campa, 2019; Sharkey & Torrats-Espinosa, 2017).

Racial gaps in mobility across cities can be explained by racial sorting into neighbourhoods, where the few whites living in a city centre have much higher mobility when there is a high share of blacks. This result suggests relative access to amenities is important, that is, even in a decaying city with a high share of black residents, existing amenities may disproportionately favour access by the few white residents who remain in the city centre. Furthermore, suburbanisation predicts differences in white male mobility suggesting a white man living in a city with a low rate of suburbanisation has better access to economic opportunities in the city centre relative to a white man living in the suburbs. Therefore, while lower suburbanisation is associated with better mobility overall, it is also predictive of better mobility for whites, perhaps due to the greater stock of economic opportunities that are generally found in a city centre. Further, I find incarceration, arrests and policing are predictive of both racial gaps in mobility and of differences between white men, in line with my main IV findings. Interestingly, policing does not appear to influence white men however is strongly associated with differences in black men's mobility outcomes, where a black men living in a city that is more strongly policed tends to have much lower mobility.

To conclude, white male mobility is responsive to most mechanisms while the only variable that significantly predicts differences in black male mobility is policing. Racial gaps in mobility are driven by racial segregation in suburbanised and high crime neighbourhoods. While this analysis of mechanisms is important for policy implications, estimated mediation effects presented in this section, albeit correlational, suggest the indirect effect of violent crime on intergenerational mobility is relatively small. The largest driver of poor intergenerational mobility in U.S. cities remains the direct effect of violent crime.

Chapter 6

Threats to Validity

In this chapter I examine potential threats to the validity of my identification strategy. First I conduct a placebo test to ensure lead poisoning only affects trends in violent crime by assessing whether soil pH influences rates of property crime. Next I study whether lead has a direct effect on my outcome through a reduction in cognitive abilities. Then I also test whether my instrument, soil pH, directly affects mobility through a reduction in agricultural production in bad soil cities. Finally I test an alternative definition of my instrument by predicting the effect of soil pH on intergenerational mobility using a cubic function of the continuous pH variable. I can conclude that the tests in this chapter do not provide evidence against the validity of my identification strategy.

6.1 Placebo test of soil pH on non-violent crimes

This section tests whether good soil affects non-violent crime rates. The medical and health literature states that exposure to lead can reduce impulse control and increase both impulsiveness and aggression (Mason, Harp & Han, 2014; Lanphear, 2015). Thus, lead is expected to most likely influence violent crime rates as most violent crimes, with the exception of some murder offences, are characterised by their impulsivity.

Table 16 explores which crimes are affected by lead by using the interaction between the good soil dummy and tetraethyl lead use lagged by 19 years. I control for non-violent crimes when estimating the effect of lead on violent crimes, and similarly, control for violent crimes when estimating the effect of lead on non-violent crimes. As expected, lead has a significant effect on all categories of violent crimes, most likely due to their impulsive or aggressive nature. Good soil cities have lower rates of violent crime relative to bad soil cities across all post-treatment years, that is, from 1960. In contrast, non-violent crimes, defined as the sum of burglary, larceny and vehicle theft, are not significantly affected by lead. Lead also has no significant impact on either burglary or larceny rates when tested individually. Rates of vehicle theft are an exception here, with good soil cities experiencing a 0.55 decrease in vehicle theft per 1,000 people across years 1960 to 2014. This may be due to vehicle theft crimes being also impulsive and largely opportunistic, however non-aggressive in nature unlike violent crimes, and therefore, unlikely to affect mobility outcomes in the long run due to their reduced severity.

This placebo test confirms that only violent and aggressive crimes are affected by lead poisoning, supporting my main hypothesis that violent crimes specifically deteriorate neighbourhood amenities and reduce mobility. Interestingly, despite fear surrounding the war on drugs (Skogan, 1986), I show in Section 5.2.2 that drug crimes are not influencing intergenerational mobility. Rather, a society marked by violent crime is more likely to respond by reducing investment into amenities and public goods, perhaps because violent crimes are characterised by their severe and aggressive nature. By threatening social norms and order, these crimes may spark greater fear in a society. On an individual-level, recidivism rates for violent offenders are almost always higher than non-violent offenders (Aharonia et al., 2013), suggesting deeper cognitive or behavioural problems that is a signal of long term persistent deviancy. Therefore, evidence presented in this section provides strong motivation behind how low mobility areas are defined by high violent crime.

Table 16: Effect of lead on different crimes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total violent	Murder	Rape	Robbery	Assault	Total non-violent	Burglary	Larceny	Vehicle theft
Good soil x lead	-2.3398***	-0.0262***	-0.1095***	-1.0722***	-3.0518***	0.7725	-0.3630	1.6890	-0.5534**
	(0.1717)	(0.0028)	(0.0106)	(0.1085)	(0.3611)	(1.5822)	(0.6328)	(0.8651)	(0.2006)
Constant	-1.4684***	-0.0001	0.0987***	-1.5735**	3.1625*	40.2630***	7.8382***	30.9937***	1.4310***
	(0.4149)	(0.0052)	(0.0219)	(0.4897)	(1.3815)	(2.5947)	(1.0851)	(1.2379)	(0.3054)
Observations	13421	13421	13308	13421	13421	13421	13421	13421	13421
R^2	0.574	0.333	0.533	0.522	0.624	0.612	0.644	0.476	0.536
Adjusted R^2	0.568	0.323	0.527	0.515	0.619	0.607	0.639	0.469	0.530
F	469.031	300.519	259.504	376.244	179.064	148.269	235.102	47.846	369.492
C.region x year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control NVC	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Control VC	No	No	No	No	No	Yes	Yes	Yes	Yes

Notes: All crimes are per 1,000 people in city centre. Total violent: sum of murder and non-negligent manslaughter, total robberies, rape and aggravated assaults. Total non-violent: sum of burglary, larceny and vehicle theft. Good soil x lead: dummy equals 1 if pH in the city centre is between 6.8 and 7.7 multiplied by tonnes of national tetraethyl lead use as gasoline additive 19 years prior, normalised by the maximum level. C.region x year: Census region times year fixed effects. Control NVC: control for total non-violent crime rate. Control VC: control for total violent crime rate. Period considered: annual observations from 1960 to 2014. Standard errors clustered on city-year in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Direct effect of lead on mobility

A potential threat to the exclusion restriction required for my IV model in Section 5.1 is if my instrument has a direct effect on my outcome and not through my treatment. This could occur in two ways. First, soil pH may have a direct effect on mobility through a reduction in cognitive abilities caused by lead poisoning. Second, soil pH may directly influence mobility if soil quality determines the productivity of a city's agricultural industry. I test both of these potential issues below.

Cognitive ability

Lead, proxied by soil pH, may have a direct effect on intergenerational mobility through a reduction in cognitive ability. The medical literature states that lead is associated with neurological and cognitive changes including problems with intelligence, learning and attention at the individual-level (Mason, Harp & Han, 2014). These problems can directly reduce mobility through a reduction in career prospects and capital accumulation. The discussion of educational attainment as a potential mechanism in Section 5.2.3 provides support against this argument. However, in this section I test further for the role of education, as a proxy for cognitive ability, in reducing mobility outcomes. Specifically, I test whether early education levels are significantly different across cities with different lead bioavailability.

Using data on the share of population with less than 9 years of schooling in 1990, when children in my sample are between 7 and 12 years old, I am able to get a basic indication of early-life cognitive abilities for children around the same age as those in my sample. However, as Table 17 shows, I do not find strong evidence supporting the link between cognitive ability and intergenerational mobility at the neighbourhood-level, as higher early education is not predictive of better mobility outcomes in good soil cities. This result supports previous research by Chetty et al. (2018b) who find that differences in cognitive ability do not explain racial mobility gaps for men. Findings of Table 17 provide support for the validity of the exclusion restriction required for my IV model. However, future studies may research the link between lead, ability and mobility at an individual-level, perhaps by looking into individual lead in blood levels and utilising better measures of cognitive ability to ascertain whether this relationship is a valid concern.

Table 17: Effect of education as a proxy for cognitive ability on intergenerational mobility

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
<9th grade	0.128	0.082	0.051	0.021	-0.045
	(0.142)	(0.089)	(0.072)	(0.082)	(0.154)
Good soil=1	0.059**	0.058***	0.059***	0.059***	0.056
	(0.021)	(0.013)	(0.013)	(0.016)	(0.030)
Good soil =1 × <9th grade	-0.413	-0.464*	-0.509*	-0.556	-0.592
	(0.362)	(0.190)	(0.197)	(0.302)	(0.622)
Constant	0.344***	0.428***	0.487***	0.545***	0.654***
	(0.009)	(0.006)	(0.005)	(0.006)	(0.011)
Observations	549	549	549	549	549
R^2	0.082	0.065	0.041	0.023	0.013
Adjusted R^2	0.071	0.055	0.030	0.012	0.002
C.region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. <9th grade: share of population with less than 9 years of schooling in 1990. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Agricultural production

My instrument, soil pH, may also affect intergenerational mobility directly through agricultural production, which may bias my results and threaten the validity of the exclusion restriction. Bad soil cities may have lower mobility if their highly acidic or alkaline soil pH levels limit their agriculture surplus and thus restrict income from the agricultural sector. In Section 4.3 I show good and bad soil cities have similar pre-trends in their agricultural employment in 1960. Further, while the region fixed effects used in my main analysis controls for potential trends in agricultural productivity, in this section I specifically test whether soil pH influences yields of different crop types within these regions.

I regress potential yields of the top 5 agricultural products in the U.S., alfalfa, corn, cotton, soy and wheat, as measured by Curci and Masera (2019), on the good soil dummy to see whether crop yields are sensitive to acidic or alkaline soil. As my instrument relies on variation in soil pH at the top level of soil, with lead expelled by cars deposited onto and retained by surface soils (Laidlaw & Filippelli, 2008), I use the same binary definition of soil quality here to determine whether surface level soil pH is predictive of crop yields. Table 18 confirms soil quality does not influence the production of any of the major 5 crops produced in the U.S.. Therefore, since I find no significant differences in potential crop yields across cities within each region, I conclude that soil pH is unlikely to directly affect mobility through agricultural surplus, providing further support for the validity of my results.

Table 18: Effect of soil pH on different agricultural crop yields

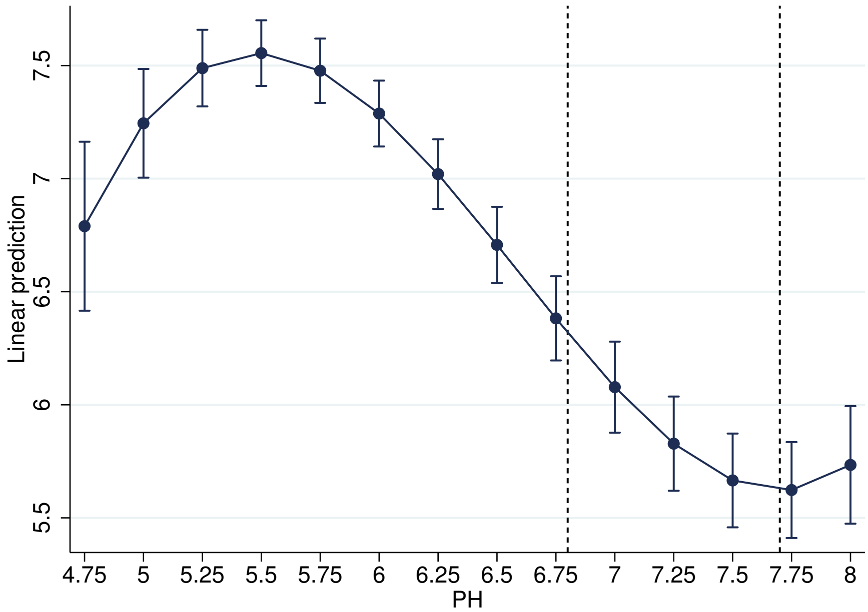
	(1) Alfalfa	(2) Corn	(3) Cotton	(4) Soy	(5) Wheat
Good soil	0.152	0.138	0.128	0.212	0.032
	(0.084)	(0.188)	(0.108)	(0.150)	(0.141)
Constant	-0.023	-0.021	-0.019	-0.032	-0.005
	(0.063)	(0.064)	(0.060)	(0.068)	(0.057)
Observations	302	302	302	302	302
R^2	0.053	0.158	0.127	0.010	0.188
Adjusted R^2	0.040	0.146	0.115	-0.004	0.177
C.region FE	Yes	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	OLS	OLS

Notes: Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. All crops are predicted yields in tonnes per hectare for years 1961 to 1990, expressed as deviations from mean. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.3 Alternative definition of instrument

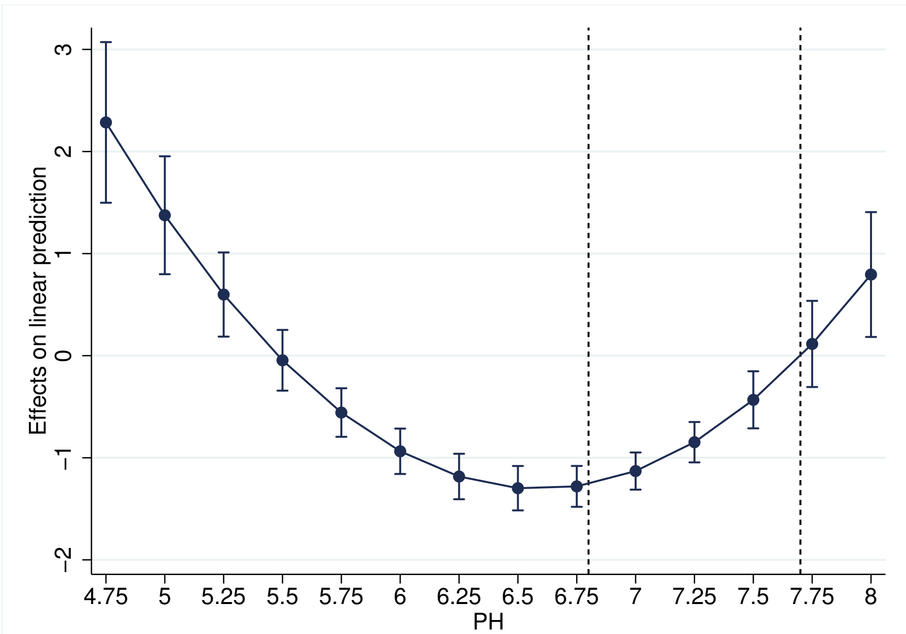
In line with chemical literature, soil pH is expected to have the lowest effect on violent criminal behaviour when close to neutral (between 6.8 and 7.7) and the highest effect when either acidic or alkaline (less than 6.8 or greater than 7.7). This relationship between soil pH and offending is clearly non-linear. Figure 6 below graphs the predicted effect of lead estimated using a cubic function of soil pH on violent crime. The effect of lead on violent crime peaks at a pH value of 5.5 and is highest when soil is highly acidic, while the predicted effect of lead on violent crime is smallest just after a pH of 7.7. Further, Figure 7 graphs the average marginal effect of soil pH on violent crime at different pH levels, estimated using a cubic function of pH. The average marginal effect of soil pH on violent crime is negative when pH is neutral and within the range of 6.8 and 7.7, as defined by the good soil binary measure. Further, marginal effects are positive for both very acidic (below 5.5) and very alkaline (above 7.7) pH levels, suggesting soil that is far from neutral is most likely to increase violent crime rates in the population.

Figure 6: Predicted effect of lead on violent crime at different soil pH levels



Notes: Graph plots predictive margins with 95% confidence intervals. Predictive margins derived after regressing violent crime on lead, lead x pH, lead x pH^2, lead x pH^3, controlling for region times year fixed effects and using standard errors clustered on city-year. Violent crime: per 1,000 people in city centre. Lead: tonnes of tetraethyl lead consumed in U.S. as gasoline additive lagged by 19 years. PH: pH of city centre.

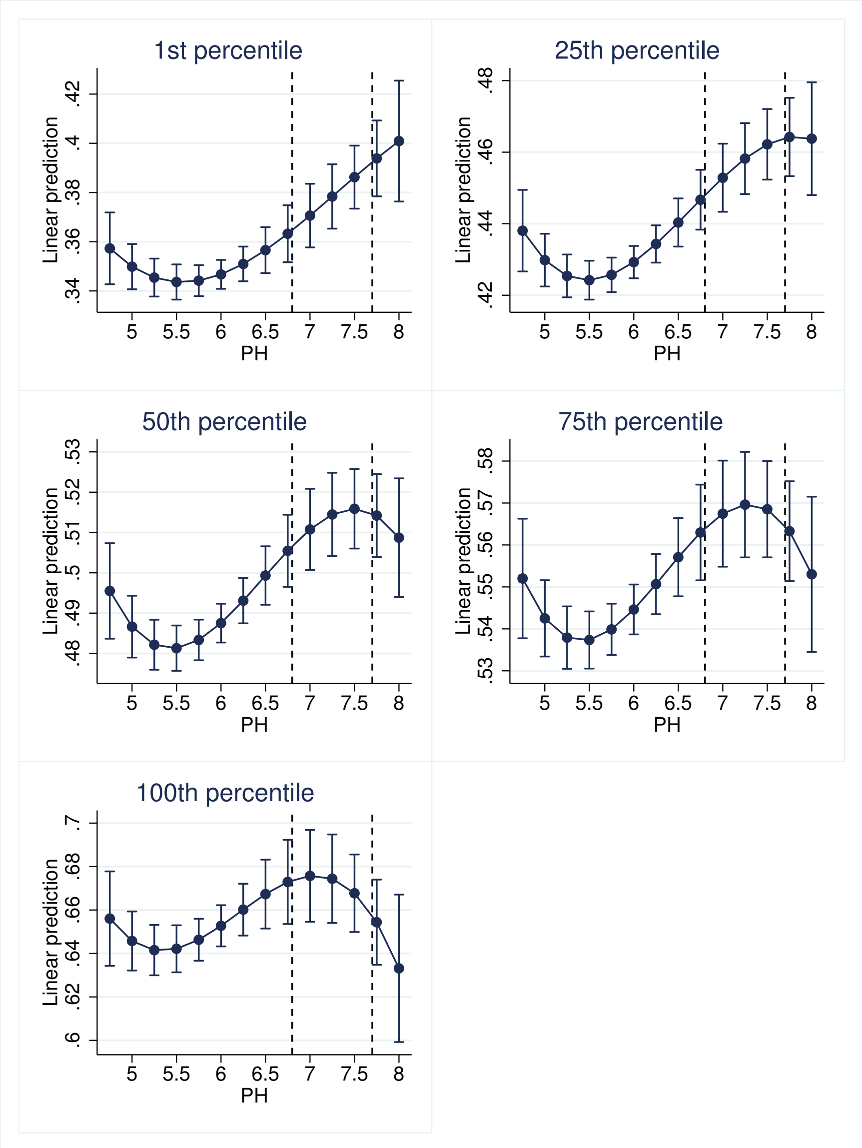
Figure 7: Average marginal effects of soil pH on violent crime at different levels



Notes: Graph plots average marginal effects of soil pH on violent crime at different levels of soil pH with 95% confidence intervals. Marginal effects derived after regressing violent crime on lead, lead x pH, lead x pH^2, lead x pH^3, controlling for region times year fixed effects and using standard errors clustered on city-year. Violent crime: per 1,000 people in city centre. Lead: tonnes of tetraethyl lead consumed in U.S. as gasoline additive lagged by 19 years. PH: pH of city centre.

Figure 8 graphs the predicted effect of soil pH, estimated using a cubic function of the continuous pH variable, on intergenerational mobility for all five income percentiles. Figure 8 shows the predicted effect of soil pH on mobility is the highest for all income groups, except the 1st percentile, when pH is close to neutral, that is, between 6.8 and 7.7. Since soil pH is predicted to increase mobility the most when pH is between this range, this continuous pH definition appears to produce similar results to the binary definition of soil quality used in the main analysis. The estimated effect predicted here is also very similar to the predicted effect of the good soil dummy on mobility visualised in Figure 10 in Appendix A.7. Further, for all income percentiles except the 1st, the peak of the predicted functions lie between the range of pH values used to define good soil earlier, while the lowest predicted effect of soil pH on mobility is around a pH value of 5.5 for all income percentiles except the 100th. This suggests that intergenerational mobility is the lowest for children exposed to very acidic soil, or soil that is highly bioavailable to lead. These results provide support for the validity of the binary definition of soil pH used in my main analysis.

Figure 8: Predicted effect of soil pH on intergenerational mobility using cubic function



Notes: Graph plots predictive margins with 95% confidence intervals. Predictive margins derived after regressing mobility on cubic function of pH, controlling for region fixed effects and using standard errors clustered on city. PH: pH of city centre.

Chapter 7

Implications and Conclusion

7.1 Policy implications

Findings of this thesis have important potential implications for different arenas of policy. The main contribution of my thesis is to show the development of different neighbourhoods is crucial in shaping intergenerational mobility outcomes. This finding along with complementary results in the neighbourhood effects literature provides strong evidence for place-based policies (Aliprantis, Carroll & Young, 2019; Chetty, Hendren & Katz, 2016). A recent evaluation of neighbourhood renewal programs has found significant reductions in crime in response to place-based initiatives in England's most deprived neighbourhoods, with positive spillover effects for neighbouring areas (Alonso, Andrews & Jorda, 2019). Similar neighbourhood programs in the U.S. have been found to increase employment and wage earnings, providing further support for efficient place-based programs (Busso, Gregory & Kline, 2013). Multi-agency initiatives intended to redevelop and invest in decaying urban areas would help to improve outcomes of residents living in places most in need. My thesis provides evidence in favour of both neighbourhood-level investments and crime reduction or prevention strategies to boost local economies and improve resident outcomes.

A key finding of this thesis – lead exposure triggers neighbourhood decay – provides evidence for continued expenditure on lead removal policies. Although the prevalence of lead poisoning in the population has significantly declined since the regulation of leaded gasoline and paint in the U.S. from the mid-1970s, lead exposure is still recognised as a public health issue, with exposure at low levels producing harmful long run impacts (CDC, 2012). Billings and Schnepel (2018) conduct an evaluation of early life interventions for lead-poisoned children in the U.S., including lead remediation treatment, nutritional and medical assessments, and case management services. The authors find long run impacts including reductions in anti-social behaviour and improvements in educational performance of treated children. My thesis supports this literature and argues the importance of prevention and treatment of lead poisoning. Furthermore, there are important implications associated with lead's heavy concentration in disadvantaged communities. Findings of this thesis indicate that black communities are particularly vulnerable to lead toxicity and experience a greater economic burden associated with exposure, a result carrying considerable implications for both public health and welfare equity.

Furthermore, racial disparities in intergenerational mobility identified in this thesis have substantial implications for welfare and income equality. Reducing racial disparities in mobility in the future will require reducing intergenerational gaps for black Americans. Transient programs such as temporary cash transfers that do not affect long run outcomes are unlikely to reduce black-white gaps in income mobility (Chetty et al., 2018b). Results of my thesis suggest closing the gap in economic opportunities between black and white children would help to alleviate the racial gap in intergenerational outcomes. Policies designed to reduce residential segregation and achieve racial integration would also help to improve access to similar opportunities and quality of amenities. Moreover, while my primary analysis focuses on men, narrowing the black-white gap in male mobility would also help to reduce the racial gap for women in the long run as children's incomes typically depend on the incomes of both of their parents (Chetty et al., 2018b). Finally, my thesis has implications for the persistence of the wealth gap. While I do not directly study wealth, poor income mobility has implications for wealth accumulation across generations. Improving income mobility will have positive effects on reducing the wealth gap by, for example, increasing blacks' home ownership rates.

7.2 Limitations and future work

Potential limitations with the exclusion restriction required for my IV framework have been previously noted. Although I do not find a direct effect of lead on mobility, lead may still affect mobility on an individual-level in ways that I have not been able to observe, carrying potential implications for the transmission of health on economic status across generations (Aizer, 2017). Furthermore, lead may directly affect cognitive ability influencing human capital accumulation, which has implications for mobility outcomes in the long run. I have been unable to assess the impact of lead poisoning on intergenerational mobility through cognitive ability at the individual-level, an issue future work may study, perhaps by utilising better measures to minimise the measurement error in capturing ability. Moreover, as I cannot capture all observable changes that occur in a neighbourhood as a result of lead exposure, there may be potential limitations in quantifying the true neighbourhood decay process. Future work may study the role of other unobservable individual or family level factors such as parenting styles that may be shaping child upbringing and mobility outcomes.

While I have been successful in assessing the effect of neighbourhood changes from the 1960s on intergenerational mobility, I have been unable to study the role of historical factors prior to this period. Poor intergenerational mobility and racial inequalities in income have existed prior to the 1960s. Future researchers may develop existing limited work by considering the role of the slave trade, the Great Migration or historical discrimination in the housing market in contributing to this persistence of poor mobility in U.S. regions today (Berger, 2018; Derenoncourt, 2019; Aaronson, Hartley & Mazumder, 2019). Furthermore, it may also be interesting to study whether the recent fall in crime has led to an improvement in mobility outcomes (Ellen & O'Regan, 2010).

Finally, due to limitations in causal interpretation of mechanisms, I suggest future studies extend my analysis on mechanisms by causally identifying the effect of neighbourhood factors mediating the lead-mobility relationship. This may require researchers to identify two distinct instruments to tackle the endogeneity of both the treatment and the mediator (Frölich & Huber, 2014). Causally identifying indirect treatment effects will have important implications for policy surrounding neighbourhood effects, an interesting point I leave for future work.

7.3 Conclusion

Overall, my research has provided evidence of the important role of neighbourhoods in shaping intergenerational mobility outcomes. Previous work has identified heterogeneous mobility outcomes that differ by geography, race and gender. I extend on this literature by using soil pH levels in 302 U.S. city centres to exogenously predict lead exposure, showing that neighbourhood outcomes have diverged as a result of this environmental shock. Areas where children were exposed to high levels of lead experienced greater increases in violent crime and poorer intergenerational mobility as a result. Conversely, children raised in areas with soil that contains low levels of bioavailable lead have between 2 and 3 percentage points higher intergenerational mobility in 2014. These non-decaying cities also have a wider black-white racial gap in mobility, reaching almost 40% for the very poor, driven primarily by improved white male outcomes.

I also extend on the neighbourhood effects literature in economics by causally identifying violent crime as the primary driver of differences in neighbourhood quality. Intergenerational mobility ranks of children raised in cities with a one standard deviation increase in violent crime are between 5 and 7 percentage points lower. The effects of violent crime on mobility are especially pertinent for poor, white men and are importantly, highly predictive of racial disparities in mobility. These high crime, poor mobility areas also tend to be more racially segregated and suburbanised, and have greater incarceration, arrests and policing.

My analysis of non-causal mechanisms suggests white Americans migrating out of the city centres in response to high crime, leaving mostly blacks in high crime city centres, led to this divergence in neighbourhood amenities and contributes to racial gaps in mobility. A high share of black residents is thus ex-post predictive of poor neighbourhood quality and lower mobility. Therefore, while I find high crime is the primary driver of poor mobility, racial demographics and urban structure of cities are also important as indirectly contributing to the persistence of racial gaps in income mobility. I conclude by emphasising the implications of decaying neighbourhoods for future generations and stress the need for policies directed toward improving long run outcomes.

References

Aizer, A. (2017). The role of children's health in the intergenerational transmission of economic status. *Child Development Perspectives 11*(3), 167-172.

Aizer, A. and J. Currie (2017). Lead and juvenile delinquency: New evidence from linked birth, school and juvenile detention records. Working Paper 23392, National Bureau of Economic Research.

Aizer, A., J. Currie, P. Simon and P. Vivier (2018). Do low levels of blood lead reduce children's future test scores? *American Economic Journal: Applied Economics 10*(1), 307-341.

Aharonia, E., G. M. Vincent, C. L. Harenski, V. D. Calhoun, W. Sinnott-Armstrong, M. S. Gazzaniga and K. A. Kiehl (2013). Neuroprediction of future rearrest. *PNAS 110*(15), 6223-6228.

Akee, R., M. R. Jones and S. R. Porter (2019). Race matters: Income shares, income inequality, and income mobility for all U.S. races. *Demography 56*(3), 999-1021.

Aliprantis, D., D. Carroll and E. Young (2019). What explains neighborhood sorting by income and race? Working Paper 18-08R, Federal Reserve Bank of Cleveland.

Alonso, J. M., R. Andrews and V. Jorda (2019). Do neighbourhood renewal programs reduce crime rates? Evidence from England. *Journal of Urban Economics 110*, 51-69.

Angrist, J. D., G. W. Imbens and D. B. Rubin (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association 91*(434), 444-455.

Bacher-Hicks, A. and E. De la Campa (2019). Social costs of proactive policing: The impact of NYC's stop and frisk program on educational attainment. Working Paper.

Baum-Snow, N. (2007). Did highways cause suburbanization? *The Quarterly Journal of Economics 122*(2), 775-805.

Berger, T. (2018). Places of persistence: Slavery and the geography of intergenerational mobility in the United States. *Demography 55*(4), 1547-1565.

Berman, Y. (2019). The long run evolution of absolute intergenerational mobility. Working Paper.

Billings, S. B., D. J. Deming and S. L. Ross (2016). Partners in crime: Schools, neighborhoods and the formation of criminal networks. Working Paper 21962, National Bureau of Economic Research.

Billings, S. B. and K. T. Schnepel (2018). Life after lead: Effects of early interventions for children exposed to lead. *American Economic Journal: Applied Economics 10*(3), 315-344.

Burdick-Will, J. (2013). School violent crime and academic achievement in Chicago. *Sociology of Education 86*(4), 343-361.

Busso, M., J. Gregory and P. Kline (2013). Assessing the incidence and efficiency of a prominent place based policy. *American Economic Review 103*(2), 897-947.

Centers for Disease Control and Prevention (CDC), Advisory Committee on Childhood Lead Poisoning Prevention. *Low level lead exposure harms children: A renewed call for primary prevention*, 2012.

Chetty, R., J. N. Friedman, N. Hendren, M. R. Jones and S. R. Porter (2018a). The Opportunity Atlas: Mapping the childhood roots of social mobility. Working Paper 25147, National Bureau of Economic Research.

Chetty, R., N. Hendren, M. R. Jones and S. R. Porter (2018b). Race and economic opportunity in the United States: An intergenerational perspective. Working Paper 24441, National Bureau of Economic Research.

Chetty, R., N. Hendren, P. Kline and E. Saez (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. Working Paper 19843, National Bureau of Economic Research.

Chetty, R. and N. Hendren (2017a). The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects. *The Quarterly Journal of Economics 133*(3), 1107-1162.

Chetty, R. and N. Hendren (2017b). The impacts of neighborhoods on intergenerational mobility II: County-level estimates. *The Quarterly Journal of Economics 133*(3), 1163-1228.

Chetty, R., N. Hendren and L. F. Katz (2016). The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment. *American Economic Review 106*(4), 855-902.

Chyn, E. (2018). Moved to opportunity: The long-run effects of public housing demolition on children. *American Economic Review 108*(10), 3028-3056.

Collins, W. J. and M. H. Wanamaker (2017). Up from slavery? African American intergenerational economic mobility since 1880. Working Paper 23395, National Bureau of Economic Research.

Corak, M. (2013). Income inequality, equality of opportunity, and intergenerational mobility. *Journal of Economic Perspectives 27*(3), 79-102.

Cullen, J. B. and S. D. Levitt (1999). Crime, urban flight, and the consequences for cities. *The Review of Economics and Statistics 81*(2), 159-169.

Curci, F. and F. Masera (2019). Flight from urban blight: lead poisoning, crime and suburbanization. Working Paper.

Dahl, M. and T. DeLeire (2008). The association between children's earnings and fathers' lifetime earnings: Estimates using administrative data. Discussion Paper 1342-08, Institute for Research on Poverty.

Damm, A. P. and C. Dustmann (2014). Does growing up in a high crime neighborhood affect youth criminal behavior? *American Economic Review 104*(6), 1806-1832.

Dapul, H. and D. Laraque (2014). Lead poisoning in children. *Advances in Pediatrics 61*(1), 313-333.

Derenoncourt, E. (2019). Can you move to opportunity? Evidence from the Great Migration. Working Paper.

Deutscher, N. (2019). Place, jobs, peers and the importance of the teenage years: Exposure effects and intergenerational mobility. Forthcoming, American Economic Journal: Applied Economics.

Dobbie, W., H. Grönqvistz, S. Niknami, M. Palme and M. Priksk (2018). The intergenerational effects of parental incarceration. Working Paper 24186, National Bureau of Economic Research.

Ellen, I. G. and K. O'Regan (2010). Crime and urban flight revisited: The effect of the 1990s drop in crime on cities. *Journal of Urban Economics 68*(3), 247-259.

Farrington, D. P. (1986). Age and crime. *Crime and Justice 7*, 189-250.

Feigenbaum, J. J. and C. Muller (2016). Lead exposure and violent crime in the early twentieth century. *Explorations in Economics History 62*, 51-86.

Franken, I. H. A., J. W. van Strien, I. Nijs and P. Muris (2008). Impulsivity is associated with behavioral decision-making deficits. *Psychiatry Research 158*(2), 155-163.

Frölich, M. and M. Huber (2014). Direct and indirect treatment effects: causal chains and mediation analysis with instrumental variables. Discussion Paper 8280, Institute of Labor Economics.

Gershenson, S. and E. Tekin (2018). The effect of community traumatic events on student achievement: Evidence from the Beltway Sniper attacks. *Education Finance and Policy 13*(4), 513-544.

Hunt, A., D. L. Johnson and D. A. Griffith (2006). Mass transfer of soil indoors by track-in on footwear. *Science of the Total Environment 370*(2-3), 360-371.

Hirschi, T. and M. Gottfredson (1983). Age and the explanation of crime. *American Journal of Sociology 89*(3), 552-584.

IPUMS National Historical Geographic Information System (NHGIS): Version 14.0 [Database]. Institute for Social Research and Data Innovation, Minneapolis, 2019.

Keele, L., D. Tingley and T. Yamamoto (2015). Identifying mechanisms behind policy interventions via causal mediation analysis. *Journal of Policy Analysis and Management 34*(4), 937-963.

Lacoe, J. R. (2015). Unequally safe: The race gap in school safety. *Violence and Juvenile Justice 13*(2), 143-168.

Laidlaw, M. A. S. and G. M. Filippelli (2008). Resuspension of urban soils as a persistent source of lead poisoning in children: A review and new directions. *Applied Geochemistry 23*(8), 2021-2039.

Lanphear, B. P. (2015). The impact of toxins on the developing brain. *Annual Review of Public Health 36*(1), 211-230.

Legewie, J. and J. Fagan (2019). Aggressive policing and the educational performance of minority youth. *American Sociological Review 84*(2), 220-247.

Liu, S. (2019). Incarceration of African American men and the impacts on women and children. Working Paper.

Manduca, R. and R. J. Sampson (2019). Punishing and toxic neighborhood environments independently predict the intergenerational social mobility of black and white children. *PNAS 116*(16), 7772-7777.

Mason, L. H., J. P. Harp and D. Y. Han (2014). Pb neurotoxicity: Neuropsychological effects of lead toxicity. *BioMed Research International 2014*, 1-8.

Mazumder, B. (2005). Fortunate sons: New estimates of intergenerational mobility in the United States using social security earnings data. *The Review of Economics and Statistics 87*(2), 235-255.

Muller, C., R. J. Sampson and A. S. Winter (2018). Environmental inequality: The social causes and consequences of lead exposure. *Annual Review of Sociology 44*(20), 1-20.

Nevin, R. (2007). Understanding international crime trends: The legacy of preschool lead exposure. *Environmental Research 104*(3), 315-336.

Nriagu, J. O. (1990). The rise and fall of leaded gasoline. *The Science of the Total Environment 92*, 13-28.

Reyes, J. W. (2015). Lead exposure and behavior: Effects on antisocial and risky behaviour among children and adolescents. *Economic Inquiry 53*(3), 1580-1605.

Rothstein, R. (2018). Inequality of educational opportunity? Schools as mediators of the intergenerational transmission of income. Working Paper 24537, National Bureau of Economic Research.

Sampson, R. J. and A. Winter (2016). The racial ecology of lead poisoning: Toxic inequality in Chicago neighborhoods, 1995-2013. *DuBois Review Social Science Research on Race 13*(2), 261-283.

Sharkey, P. (2010). The acute effect of local homicides on children's cognitive performance. *PNAS 107*(26), 11733-11738.

Sharkey, P. (2016). Neighborhoods, cities, and economic mobility. *Russell Sage Foundation Journal of the Social Sciences 2*(2), 159-177.

Sharkey, P. and G. Torrats-Espinos (2017). The effect of violent crime on economic mobility. *Journal of Urban Economics 102*(1), 22-33.

Sharkey, P., N. Tirado-Strayer, A. V. Papachristos and C. C. Raver (2012). The effect of local violence on children's attention and impulse control. *American Journal of Public Health 102*(12), 2287-2293.

Skogan, W. (1986). Fear of crime and neighborhood change. *Crime and Justice 8*, 203-229.

Sviatschi, M. M. (2019). Making a narco: Childhood exposure to illegal labor markets and criminal life paths. Working Paper.

Taylor, M. P., M. K. Forbes, B. Opeskin, N. Parr and B. P. Lanphear (2016). The relationship between atmospheric lead emissions and aggressive crime: An ecological study. *Environmental Health 15*(23), 1-10.

United States Department of Commerce, Bureau of the Census, Current Population Survey, 2018.

United States Department of Justice, F.B.I. Uniform Crime Reporting Program Data: Offenses Known and Clearances by Arrest, 1960-2014.

United States Department of Justice, F.B.I. Uniform Crime Reporting Program Data: Arrests by Age, Sex, and Race, 1974-2016.

Wright, J. P., K. N. Dietrich, M. D. Ris, R. W. Hornung, S. D. Wessel, B. P. Lanphear, M. Ho and M. N. Rae (2008). Association of prenatal and childhood blood lead concentrations with criminal arrests in early adulthood. *PLoS Medicine 5*(5), 732-740.

Appendix

A.1 OLS estimation

Table 19: OLS regression of violent crime and intergenerational mobility

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
Panel A: Black and white males					
Violent crime	-0.0090***	-0.0083***	-0.0080***	-0.0079***	-0.0060
	(0.0023)	(0.0019)	(0.0020)	(0.0024)	(0.0036)
Constant	0.3575***	0.4378***	0.4945***	0.5502***	0.6548***
	(0.0025)	(0.0019)	(0.0019)	(0.0023)	(0.0038)
Observations	549	549	549	549	549
R^2	0.070	0.052	0.030	0.015	0.006
Adjusted R^2	0.063	0.045	0.023	0.008	-0.002
F	15.000	19.856	16.767	11.150	2.860
Panel B: Black and white females					
Violent crime	0.0071*	0.0040	0.0017	-0.0014	-0.0070*
	(0.0028)	(0.0024)	(0.0024)	(0.0025)	(0.0035)
Constant	0.3431***	0.4032***	0.4492***	0.4993***	0.6020***
	(0.0022)	(0.0016)	(0.0017)	(0.0022)	(0.0038)
Observations	547	547	547	547	547
R^2	0.072	0.076	0.047	0.033	0.026
Adjusted R^2	0.065	0.069	0.040	0.025	0.018
F	6.601	2.805	0.528	0.294	3.927
C.region FE	Yes	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	OLS	OLS

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Violent crime: sum of violent crime per capita in city centre for years 1978-2014 expressed as deviations from mean. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.2 Event study

Table 20: Event study results

	Violent crime		Violent crime		Violent crime		Violent crime
1960	-0.1819	1974	-1.4839**	1988	-2.9411***	2002	-1.7009*
	(0.1902)		(0.5254)		(0.8062)		(0.6896)
1961	-0.1969	1975	-2.1705***	1989	-3.5235***	2003	-1.7296*
	(0.1946)		(0.5696)		(0.8543)		(0.6957)
1962	-0.3656	1976	-2.2452***	1990	-4.2840***	2004	-1.6829*
	(0.2077)		(0.5095)		(0.8246)		(0.6727)
1963	-0.3515	1977	-1.9723***	1991	-4.6145***	2005	-1.8411**
	(0.1829)		(0.5290)		(0.9284)		(0.7087)
1964	-0.4158	1978	-2.1368***	1992	-4.2214***	2006	-1.9112*
	(0.2212)		(0.5470)		(1.2324)		(0.7501)
1965	-0.6087**	1979	-2.4115***	1993	-3.8207**	2007	-1.8396*
	(0.2016)		(0.5742)		(1.3066)		(0.7399)
1966	-0.6218*	1980	-3.0259***	1994	-3.6621***	2008	-1.9207***
	(0.2516)		(0.6399)		(0.9689)		(0.5704)
1967	-0.8310**	1981	-3.0854***	1995	-2.8603**	2009	-1.6115**
	(0.2825)		(0.6165)		(0.9058)		(0.5295)
1968	-1.2025***	1982	-2.6280***	1996	-3.0828***	2010	-1.6477**
	(0.3516)		(0.6040)		(0.7349)		(0.5014)
1969	-1.3642***	1983	-2.6709***	1997	-3.3152***	2011	-1.4943**
	(0.3925)		(0.5918)		(0.6740)		(0.4949)
1970	-1.3496**	1984	-2.9575***	1998	-3.4923***	2012	-1.3219*
	(0.4367)		(0.5998)		(0.6499)		(0.6129)
1971	-1.4161**	1985	-3.2280***	1999	-2.6910***	2013	-1.4582*
	(0.4726)		(0.6325)		(0.5577)		(0.5866)
1972	-1.6374***	1986	-3.2214***	2000	-2.4100***	2014	-1.3981*
	(0.4743)		(0.7626)		(0.5620)		(0.6014)
1973	-1.4730**	1987	-3.2725***	2001	-2.2164***	.	.
	(0.4742)		(0.7911)		(0.5894)		.

Notes: Event study regresses violent crime rate in each year on year dummies which equal 1 if year is as indicated and good soil equals 1. Violent crime: violent crime per 1,000 people in city centre. Good soil: dummy equals 1 if pH in city centre is between 6.8 and 7.7. Region specific year fixed effects have been used. Standard errors clustered on city-year in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.3 Balancing test of covariates

Table 21: Balancing test for levels and trends in observable characteristics of cities

	(1) Mean	(2) Levels: All cities	(3) Levels: Inside region	(4) Trend: All cities	(5) Trend: Inside region
Population CC (60-50)	203932.6	-77388.9	-43527.3	31978.21	12829.2
Population MSA (60-50)	429788.5	-175395.4	-108323.8	29964.61	-632.77
Area CC (50)	27.59	3.44	-.05	.	.
Area MSA (50)	2063.0	708.91	-260.77	.	.
Pop. density (sq m) MSA (60-50)	198.12	-105.89*	-63.58	12.40	4.91
Median family income CC (60-50)	22854.16	1950.12**	905.53	58.83	-602.45
Median family income MSA (60-50)	21419.86	1806.86**	955.91	-317.33	-908.04
Median age MSA (60-50)	29.48	-.93	-.80	-1.02	-.70
Gini coefficient CC (60-50)	.34	.018**	.012	-.002	-.002
% Blacks CC (60)	13.36	-7.62***	-4.62*	.	.
% Blacks MSA (60)	9.41	-5.38***	-3.28*	.	.
% Pop. not white MSA (60-50)	9.89	-5.06***	-3.53*	.53	.41
No. of families MSA (60-50)	110961.0	-42028.5	-25976.06	6004.64	31.40
% Pop. 5 years old MSA (60-50)	1.11	.06**	.03	.80***	.76**
% Pop. 65 or older MSA (60-50)	7.80	-.94*	-.83*	-.51	-.35
No. employed CC (60-50)	84086.97	-33831.63	-18731.17	14982.81	7062.85
Unemployment rate MSA (60)	5.15	.25	-.08	.	.
Civilian labour force MSA (60-50)	175928.7	-73576.68	-42138.28	18251.84	4889.32
% Occupied housing + auto CC (60)	81.75	5.03***	3.11**	.	.

Table 21 - continued from previous page

Median house value MSA (60)	64630.24	4843.12	1204.55	.	.
Median gross rent per unit MSA (60)	385.75	26.83*	12.98	.	.
No. occupied units MSA (60-50)	123769.5	-42242.52	-27103.64	6288.86	-478.49
No. owner occupied units MSA (60-50)	64946.27	-19475.85	-16388.71	-3997.35	-5838.26
No. housing units MSA (60-50)	130876.3	-44228.75	-28994.62	5363.57	-1906.47
% Public transport to work MSA (60)	6.80	-4.03***	-3.00***	.	.
% 25+ complete high school MSA (60-50)	34.32	9.90***	5.59***	.43	.72
% 25+ with <5 yrs school MSA (60-50)	11.33	-4.53***	-3.37**	1.07	.80
Median yrs school MSA (60-50)	9.56	1.42***	.81***	-.14	-.007
Highway expenditure ($1000) CC (60)	3307.14	-1507.37	-747.06	.	.
Employment rate MSA (60-50)	.37	-.01	.0004	.002	-.004
Employment rate agriculture MSA (60-50)	.03	.006	.005	-.0007	-.0004
Employment rate construction MSA (60-50)	.03	.006***	.004**	-.0006	-.0001
Employment rate finance MSA (60-50)	.01	.001	.001	.0007	.0005
Employment rate manufacturing MSA (60-50)	.09	-.06***	-.04***	.008	.002
Employment rate transport MSA (60-50)	.03	.005	.004	-.002	-.002
Employment rate trade MSA (60-50)	.07	.01***	.013***	-.003	-.003

Notes: Number in parentheses refers to year of data. The first number in parentheses, if two numbers are present, refers to the year the trend coefficient has been taken. Mean: mean value of variable in earliest year in parentheses, which is also the year the level coefficient has been taken. Level: All cities: coefficient obtained regressing variable on good soil dummy. Level: Inside region: coefficient obtained regressing variable on good soil dummy controlling for Census region fixed effects. Trend: All cities: coefficient obtained regressing variable on good soil dummy interacted by year in which trend coefficient has been taken, controlling for year fixed effects. Trend: Inside region: coefficient obtained regressing variable on good soil dummy interacted by year in which trend coefficient has been taken, controlling for Census region times year fixed effects. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. CC: city centre. MSA: Metropolitan Statistical Area. Standard errors clustered on city for levels test and city-year for trends test have been used. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21 above presents results for the balancing test of both levels and trends in observable pre-treatment covariates of cities required for my exogeneity assumption in Section 4.3. Various demographic, geographic and economic variables are tested at both the city centre and MSA levels to determine whether good and bad soil cities significantly differ in characteristics that may influence mobility. While it appears cities in the same region differ across quite a few variables in their 1960 levels (Column 3), only two variables measured at the city centre level are unbalanced: percentage of population that is black and percentage of housing that is occupied and has at least one car. Since violent crime, soil pH and mobility measures are all at the city centre level, I report the reduced form estimation controlling for these two variables in Table 22. While the significance and magnitude of my reduced form results decrease slightly with the inclusion of these controls, coefficients on the variable of interest (good soil) remain robust in their direction of predicted effect. Results are in particular robust for children at or below the 50th percentile. Furthermore and importantly, only one variable exhibits a different trend across the decade prior to treatment start: proportion of the population younger than 5 years old. In Table 23, I show my main result is robust to the inclusion of this unbalanced pre-treatment trend in the young population size.

Table 22: Reduced form regression with controls for unbalanced levels

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Good soil	0.0301*	0.0270**	0.0247**	0.0224	0.0190
	(0.0127)	(0.0088)	(0.0092)	(0.0119)	(0.0206)
Constant	0.3870***	0.4974***	0.5761***	0.6536***	0.7951***
	(0.0758)	(0.0511)	(0.0442)	(0.0498)	(0.0864)
Observations	427	427	427	427	427
R^2	0.055	0.049	0.035	0.024	0.016
Adjusted R^2	0.042	0.035	0.021	0.010	0.002
F	2.878	5.289	6.020	4.971	2.049
C. region FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Controls: percent of population black and percent of housing occupied with at least one automobile in city centre in 1960. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Reduced form regression with controls for unbalanced trends

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
Good soil	0.0262*	0.0239**	0.0222*	0.0204	0.0178
	(0.0118)	(0.0082)	(0.0087)	(0.0114)	(0.0197)
Constant	0.2296***	0.3326***	0.4046***	0.4749***	0.6125***
	(0.0277)	(0.0220)	(0.0236)	(0.0289)	(0.0457)
Observations	433	433	433	433	433
R^2	0.081	0.065	0.040	0.022	0.008
Adjusted R^2	0.070	0.054	0.029	0.010	-0.004
F	14.932	15.835	11.387	6.349	1.365
C. region FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Controls: percent of population 5 years old or younger in MSA in 1960. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.4 Reduced form results for females

Here I present reduced form results for a female sample, where I show that lead exposure, proxied by soil pH, is not predictive of differences in intergenerational mobility of females. This is also true when you restrict the female sample to either white or black race. This result indicating the mobility of women is not sensitive to neighbourhood decay suggests a key point for future research: what predicts female mobility?

Table 24: Effect of lead on intergenerational mobility, females

	(1) 1st percentile	(2) 25th percentile	(3) 50th percentile	(4) 75th percentile	(5) 100th percentile
Panel A: White and black females					
Good soil	0.0124	0.0045	-0.0019	-0.0072	-0.0200
	(0.0083)	(0.0055)	(0.0057)	(0.0076)	(0.0144)
Constant	0.3422***	0.4030***	0.4496***	0.5001***	0.6039***
	(0.0024)	(0.0018)	(0.0018)	(0.0022)	(0.0039)
Observations	547	547	547	547	547
R^2	0.056	0.064	0.045	0.034	0.024
Adjusted R^2	0.049	0.057	0.038	0.027	0.017
F	2.239	0.654	0.113	0.886	1.936
Panel B: Black females					
Good soil	0.0195	0.0004	-0.0146	-0.0282	-0.0595
	(0.0149)	(0.0073)	(0.0106)	(0.0177)	(0.0361)
Constant	0.3391***	0.4032***	0.4538***	0.4996***	0.6047***
	(0.0034)	(0.0019)	(0.0025)	(0.0039)	(0.0078)
Observations	245	245	245	245	245
R^2	0.051	0.051	0.041	0.039	0.040
Adjusted R^2	0.035	0.035	0.025	0.023	0.024
F	1.709	0.004	1.902	2.541	2.711
Panel C: White females					
Good soil	0.0079	0.0067	0.0058	0.0046	0.0024
	(0.0082)	(0.0070)	(0.0063)	(0.0058)	(0.0063)
Constant	0.3448***	0.4028***	0.4462***	0.5006***	0.6033***
	(0.0027)	(0.0023)	(0.0021)	(0.0019)	(0.0023)
Observations	302	302	302	302	302
R^2	0.071	0.078	0.113	0.190	0.290
Adjusted R^2	0.058	0.066	0.101	0.179	0.281
F	0.935	0.911	0.827	0.614	0.140
C. region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in the city centre is between 6.8 and 7.7. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

A.5 Test of coefficient equality

Table 25: Results of tests for coefficient equality

	Panel A	Panel B	Panel C
Column (1) – Column (2)	0.0000	0.0000	0.1620
Column (2) – Column (3)	0.0000	0.0000	0.0023
Column (3) – Column (4)	0.0000	0.0000	0.3819
Column (4) – Column (5)	0.0000	0.0000	0.6837

Notes: Reported statistics are p-values for test of equality between coefficients on the good soil variable in adjacent columns indicated in Table 6.

A.6 Other summary statistics

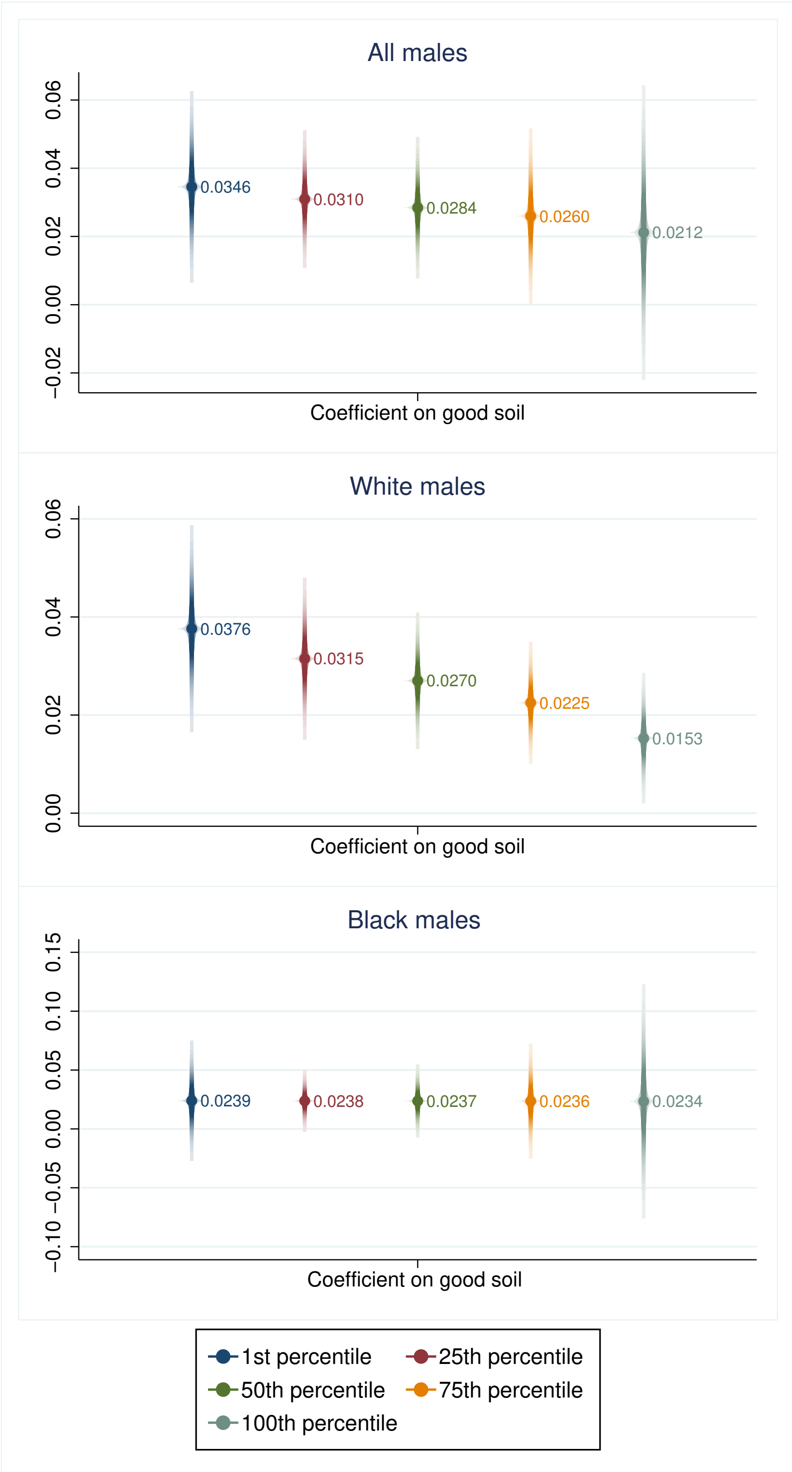
Table 26: Summary statistics for neighbourhood outcomes

	Mean (Std. Dev.)	Min	Max
Share black	0.1807 (0.1730)	0.0001	0.9240
Share white	0.7478 (0.1837)	0.0548	0.9976
Population CC	0.9695 (1.6553)	0.0071	40.0527
Officers employed	2.6209 (4.8199)	0.0	113.9154
Officers assaulted	0.2743 (0.4475)	0.0	11.6602
Incarceration	2.9557 (2.7393)	0.0	66.7256
Violent arrests	4.5403 (3.3542)	0.0	54.5406
Disorder arrests	18.7130 (26.0380)	0.0	529.1779
Drug arrests	5.1954 (6.0783)	0.0	127.5278
High school	55.0432 (17.8385)	14.6	90.6
College	15.9073 (6.2880)	5.0733	44.0
House value	86264.11 (37470.09)	32060.48	388822.90
Unemployment	5.5864 (1.8761)	1.6	14.8709
Married	79606.63 (215873.60)	2225.0	3633097.0

Notes: Mean: mean value of variable across period 1960 to 2014. Values reported are before standardising. Share black: fraction of city centre residents of black race. Share white: fraction of city centre residents of white race. Population CC: share of population living in city centre relative to suburbs. Officers employed: police officers employed per 1,000 people. Officers assaulted: police officers assaulted per 1,000 people. Incarceration: violent crime offences cleared per 1,000 people. Violent arrests: violent crime arrests per 1,000 people. Disorder arrests: sum of drunkenness, disorder conduct, driving under influence, curfew loiter, vagrancy and vandalism arrests per 1,000 people. Drug arrests: sum of drug sale and possession arrests per 1,000 people. High school: share of those 25 or older with high school diploma. College: share of those 25 or older with 4 year college degree. House value: median single family house value in city. Unemployment rate: in city. Married: number of people in city that is married.

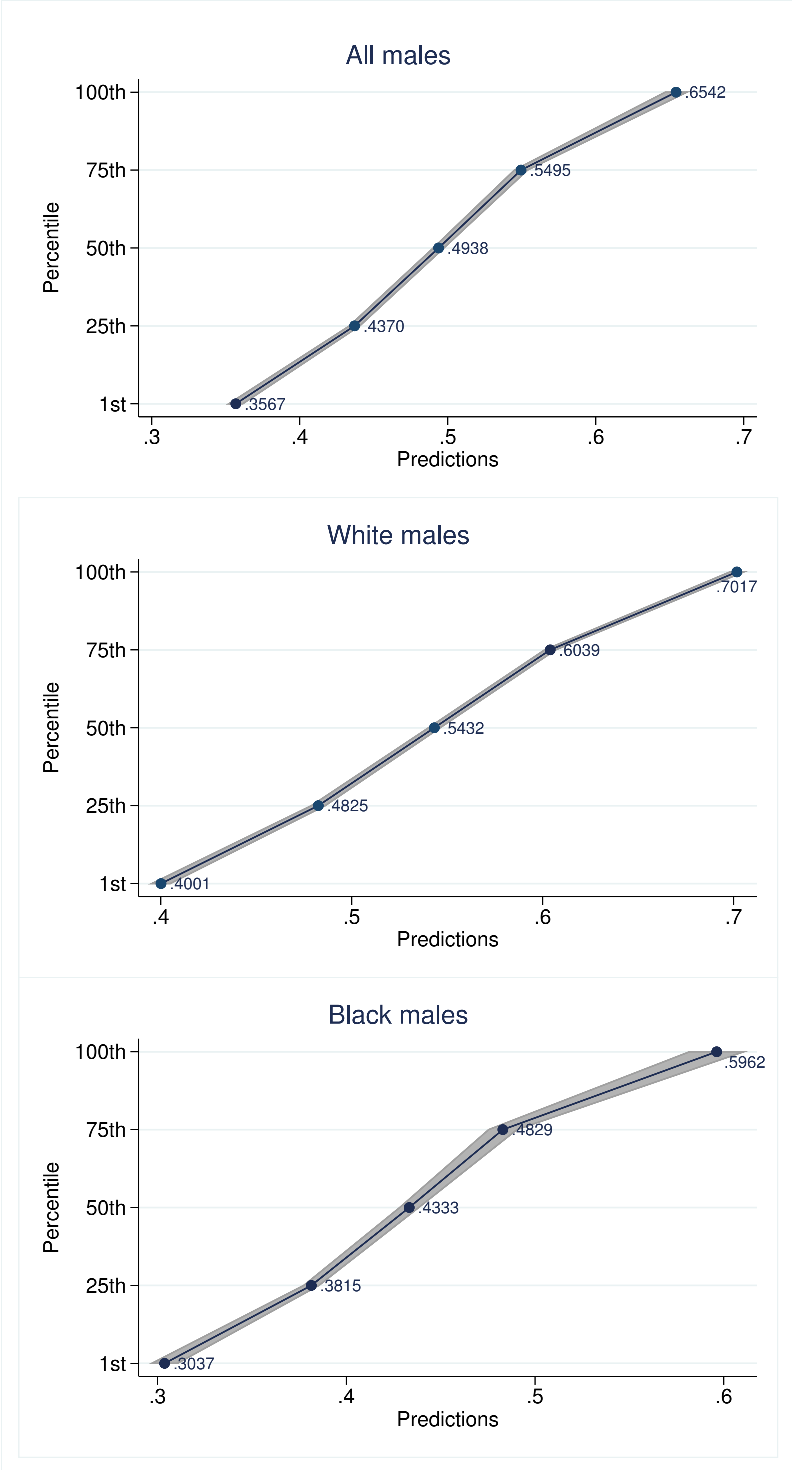
A.7 Reduced form figures

Figure 9: Plot of reduced form coefficients



Notes: Graph plots coefficients on the effect of good soil on intergenerational mobility and 95% confidence intervals as reported in Table 6.

Figure 10: Predicted effect of good soil on intergenerational mobility



Notes: Graph plots predictive margins with 95% confidence intervals. Predictive margins are for the effect of good soil on intergenerational mobility as reported in Table 6.

A.8 Within-race mechanism analysis

Table 27: Heterogeneity of responses to mechanisms by race: Effect of neighbourhood outcomes on intergenerational mobility

	(1)	(2)	(3)	(4)	(5)
	1st percentile	25th percentile	50th percentile	75th percentile	100th percentile
Panel A: Share of blacks living in city centre					
A.1: White only					
Share black	-0.0306	-0.0204	-0.0128	-0.0053	0.0068
	(0.0187)	(0.0135)	(0.0115)	(0.0122)	(0.0175)
Good soil	0.0351***	0.0299***	0.0260***	0.0221***	0.0158**
	(0.0081)	(0.0063)	(0.0053)	(0.0048)	(0.0054)
Constant	0.4006***	0.4818***	0.5417***	0.6016***	0.6980***
	(0.0049)	(0.0034)	(0.0027)	(0.0027)	(0.0042)
Observations	301	301	301	301	301
A.2: Black only					
Share black	-0.0080	0.0023	0.0092	0.0157	0.0307
	(0.0174)	(0.0124)	(0.0160)	(0.0224)	(0.0401)
Good soil	0.0232	0.0242*	0.0248*	0.0254	0.0268
	(0.0199)	(0.0102)	(0.0121)	(0.0191)	(0.0390)
Constant	0.3028***	0.3781***	0.4283***	0.4763***	0.5861***
	(0.0065)	(0.0042)	(0.0056)	(0.0081)	(0.0150)
Observations	246	246	246	246	246

Table 27 - continued from previous page

Panel B: Share of whites living in city centre					
B.1: White only					
Share white	0.0049	0.0042	0.0036	0.0031	0.0022
	(0.0174)	(0.0127)	(0.0108)	(0.0110)	(0.0152)
Good soil	0.0374***	0.0313***	0.0268***	0.0223***	0.0151**
	(0.0082)	(0.0064)	(0.0053)	(0.0048)	(0.0052)
Constant	0.3909***	0.4747***	0.5365***	0.5983***	0.6978***
	(0.0125)	(0.0094)	(0.0081)	(0.0082)	(0.0109)
Observations	301	301	301	301	301
B.2: Black only					
Share white	-0.0089	-0.0110	-0.0123	-0.0136	-0.0166
	(0.0207)	(0.0136)	(0.0175)	(0.0252)	(0.0466)
Good soil	0.0249	0.0249*	0.0249*	0.0249	0.0249
	(0.0201)	(0.0102)	(0.0121)	(0.0192)	(0.0393)
Constant	0.3069***	0.3860***	0.4388***	0.4893***	0.6047***
	(0.0133)	(0.0087)	(0.0107)	(0.0152)	(0.0282)
Observations	246	246	246	246	246
Panel C: City centre population					
C.1: White only					
Population CC	0.0075***	0.0055***	0.0039***	0.0024*	-0.0001
	(0.0013)	(0.0009)	(0.0009)	(0.0012)	(0.0017)
Good soil	0.0331***	0.0283***	0.0247***	0.0211***	0.0153**
	(0.0085)	(0.0066)	(0.0056)	(0.0049)	(0.0053)

Table 27 - continued from previous page

Constant	0.3885***	0.4734***	0.5361***	0.5986***	0.6995***
	(0.0029)	(0.0022)	(0.0018)	(0.0018)	(0.0024)
Observations	302	302	302	302	302
C.2: Black only					
Population CC	0.0038	0.0041*	0.0043	0.0045	0.0049
	(0.0024)	(0.0017)	(0.0022)	(0.0033)	(0.0060)
Good soil	0.0206	0.0201	0.0199	0.0196	0.0190
	(0.0204)	(0.0103)	(0.0125)	(0.0200)	(0.0407)
Constant	0.2982***	0.3757***	0.4274***	0.4769***	0.5899***
	(0.0038)	(0.0024)	(0.0029)	(0.0041)	(0.0077)
Observations	247	247	247	247	247
Panel D: Incarceration for violent crimes					
D.1: White only					
Incarceration	-0.0058*	-0.0054**	-0.0051**	-0.0048**	-0.0043
	(0.0027)	(0.0020)	(0.0018)	(0.0018)	(0.0025)
Good soil	0.0356***	0.0296***	0.0252***	0.0208***	0.0137**
	(0.0080)	(0.0062)	(0.0052)	(0.0047)	(0.0051)
Constant	0.3948***	0.4781***	0.5395***	0.6009***	0.6997***
	(0.0027)	(0.0020)	(0.0016)	(0.0015)	(0.0020)
Observations	300	300	300	300	300
D.2: Black only					
Incarceration	-0.0050	-0.0026	-0.0009	0.0006	0.0041
	(0.0028)	(0.0019)	(0.0026)	(0.0038)	(0.0071)

Table 27 - continued from previous page

Good soil	0.0225	0.0230*	0.0234	0.0237	0.0245
	(0.0198)	(0.0101)	(0.0121)	(0.0191)	(0.0390)
Constant	0.3019***	0.3792***	0.4308***	0.4801***	0.5928***
	(0.0036)	(0.0022)	(0.0027)	(0.0040)	(0.0077)
Observations	245	245	245	245	245
Panel E: Violent crime arrests					
E.1: White only					
Violent arrests	-0.0079***	-0.0066***	-0.0056***	-0.0046**	-0.0030
	(0.0023)	(0.0018)	(0.0016)	(0.0016)	(0.0020)
Good soil	0.0354***	0.0296***	0.0254***	0.0212***	0.0144**
	(0.0078)	(0.0061)	(0.0051)	(0.0046)	(0.0051)
Constant	0.3948***	0.4781***	0.5395***	0.6008***	0.6996***
	(0.0026)	(0.0019)	(0.0016)	(0.0015)	(0.0020)
Observations	300	300	300	300	300
E.2: Black only					
Violent arrests	-0.0047	-0.0021	-0.0003	0.0014	0.0052
	(0.0035)	(0.0020)	(0.0027)	(0.0042)	(0.0080)
Good soil	0.0235	0.0236*	0.0236*	0.0237	0.0238
	(0.0198)	(0.0101)	(0.0120)	(0.0190)	(0.0389)
Constant	0.3014***	0.3789***	0.4307***	0.4801***	0.5931***
	(0.0035)	(0.0021)	(0.0026)	(0.0039)	(0.0073)
Observations	245	245	245	245	245
Panel F: Police officers employed					

Table 27 - continued from previous page

F.1: White only					
Officers employed	-0.0010	-0.0011	-0.0012*	-0.0012*	-0.0014
	(0.0009)	(0.0007)	(0.0005)	(0.0005)	(0.0008)
Good soil	0.0374***	0.0313***	0.0267***	0.0222***	0.0149**
	(0.0082)	(0.0064)	(0.0054)	(0.0048)	(0.0052)
Constant	0.3945***	0.4778***	0.5393***	0.6007***	0.6995***
	(0.0026)	(0.0020)	(0.0016)	(0.0015)	(0.0020)
Observations	300	300	300	300	300
F.2: Black only					
Officers employed	-0.0053***	-0.0016*	0.0009	0.0033*	0.0086***
	(0.0012)	(0.0007)	(0.0009)	(0.0013)	(0.0025)
Good soil	0.0233	0.0236*	0.0238*	0.0240	0.0245
	(0.0197)	(0.0102)	(0.0120)	(0.0189)	(0.0384)
Constant	0.3012***	0.3788***	0.4306***	0.4801***	0.5933***
	(0.0034)	(0.0020)	(0.0025)	(0.0037)	(0.0070)
Observations	245	245	245	245	245
Panel G: Police officers assaulted					
G.1: White only					
Officer assaulted	-0.0042*	-0.0038*	-0.0035*	-0.0032	-0.0027
	(0.0019)	(0.0015)	(0.0014)	(0.0016)	(0.0023)
Good soil	0.0361***	0.0302***	0.0257***	0.0213***	0.0143**
	(0.0081)	(0.0063)	(0.0053)	(0.0048)	(0.0052)
Constant	0.3947***	0.4780***	0.5394***	0.6008***	0.6996***

Table 27 - continued from previous page

	(0.0027)	(0.0020)	(0.0016)	(0.0015)	(0.0020)
Observations	300	300	300	300	300
G.2: Black only					
Officers assaulted	-0.0059*	-0.0036*	-0.0020	-0.0005	0.0029
	(0.0028)	(0.0018)	(0.0025)	(0.0037)	(0.0069)
Good soil	0.0221	0.0227*	0.0230	0.0234	0.0241
	(0.0199)	(0.0101)	(0.0121)	(0.0192)	(0.0391)
Constant	0.3014***	0.3790***	0.4308***	0.4803***	0.5934***
	(0.0034)	(0.0021)	(0.0025)	(0.0037)	(0.0071)
Observations	245	245	245	245	245
Panel H: Drug crime arrests					
H.1: White only					
Drug arrests	-0.0021	-0.0014	-0.0009	-0.0004	0.0004
	(0.0022)	(0.0016)	(0.0014)	(0.0013)	(0.0018)
Good soil	0.0368***	0.0310***	0.0266***	0.0223***	0.0153**
	(0.0082)	(0.0064)	(0.0054)	(0.0049)	(0.0052)
Constant	0.3946***	0.4779***	0.5393***	0.6006***	0.6995***
	(0.0027)	(0.0020)	(0.0016)	(0.0016)	(0.0020)
Observations	300	300	300	300	300
H.2: Black only					
Drug arrests	-0.0028	0.0009	0.0033	0.0056	0.0109
	(0.0040)	(0.0023)	(0.0031)	(0.0047)	(0.0090)
Good soil	0.0238	0.0239*	0.0240*	0.0241	0.0243

Table 27 - continued from previous page

	(0.0198)	(0.0102)	(0.0120)	(0.0189)	(0.0385)
Constant	0.3010***	0.3787***	0.4305***	0.4801***	0.5934***
	(0.0034)	(0.0021)	(0.0025)	(0.0037)	(0.0070)
Observations	245	245	245	245	245
Panel I: High school attainment					
I.1: White only					
High school	0.0017*	0.0013*	0.0010**	0.0007**	0.0002
	(0.0008)	(0.0005)	(0.0003)	(0.0002)	(0.0005)
Good soil	0.0337***	0.0283***	0.0243***	0.0203***	0.0138*
	(0.0088)	(0.0071)	(0.0061)	(0.0057)	(0.0062)
Constant	0.2697***	0.3832***	0.4669***	0.5505***	0.6852***
	(0.0598)	(0.0376)	(0.0236)	(0.0181)	(0.0357)
Observations	233	233	233	233	233
I.2: Black only					
High school	0.0016*	0.0008	0.0002	-0.0003	-0.0015
	(0.0007)	(0.0005)	(0.0007)	(0.0011)	(0.0021)
Good soil	0.0316	0.0300*	0.0290*	0.0280	0.0256
	(0.0184)	(0.0116)	(0.0141)	(0.0203)	(0.0382)
Constant	0.1777**	0.3198***	0.4147***	0.5055***	0.7127***
	(0.0541)	(0.0330)	(0.0516)	(0.0793)	(0.1492)
Observations	200	200	200	200	200
Panel J: Average house value in a city					
J.1: White only					

Table 27 - continued from previous page

House values	0.0585***	0.0397***	0.0259***	0.0120	-0.0103
	(0.0103)	(0.0075)	(0.0062)	(0.0063)	(0.0088)
Good soil	0.0406***	0.0331***	0.0276***	0.0221***	0.0131*
	(0.0086)	(0.0071)	(0.0062)	(0.0058)	(0.0061)
Constant	-0.2807*	0.0200	0.2418***	0.4632***	0.8201***
	(0.1193)	(0.0861)	(0.0718)	(0.0725)	(0.1017)
Observations	233	233	233	233	233
J.2: Black only					
House values	0.0317*	0.0145	0.0030	-0.0080	-0.0331
	(0.0158)	(0.0106)	(0.0149)	(0.0219)	(0.0402)
Good soil	0.0358	0.0319**	0.0293*	0.0269	0.0212
	(0.0184)	(0.0118)	(0.0137)	(0.0192)	(0.0358)
Constant	-0.0683	0.2107	0.3969*	0.5749*	0.9816*
	(0.1823)	(0.1224)	(0.1725)	(0.2531)	(0.4652)
Observations	200	200	200	200	200
Panel K: Rates of marriage in a city					
K.1: White only					
Married	0.0102***	0.0067***	0.0042**	0.0016	-0.0026
	(0.0023)	(0.0018)	(0.0015)	(0.0015)	(0.0018)
Good soil	0.0396***	0.0328***	0.0278***	0.0228***	0.0148**
	(0.0084)	(0.0066)	(0.0055)	(0.0049)	(0.0051)
Constant	0.2862***	0.4064***	0.4951***	0.5837***	0.7264***
	(0.0250)	(0.0193)	(0.0166)	(0.0160)	(0.0198)

Table 27 - continued from previous page

Observations	302	302	302	302	302
K.2: Black only					
Married	0.0012	0.0024	0.0032	0.0040	0.0057
	(0.0035)	(0.0021)	(0.0025)	(0.0036)	(0.0069)
Good soil	0.0242	0.0244*	0.0244*	0.0245	0.0247
	(0.0197)	(0.0102)	(0.0120)	(0.0187)	(0.0381)
Constant	0.2880***	0.3530***	0.3963***	0.4378***	0.5326***
	(0.0390)	(0.0228)	(0.0271)	(0.0400)	(0.0773)
Observations	247	247	247	247	247
C. region FE	Yes	Yes	Yes	Yes	Yes

Notes: Percentile: predicted mean income rank of children grouped by parent's income percentile. Good soil: dummy equals 1 if pH in city centre is between 6.8 and 7.7. Share black: fraction of city centre residents of black race. Share white: fraction of city centre residents of white race. Population CC: share of population living in city centre relative to suburbs. Incarceration: rate of violent crime offences cleared per 1,000 people, deviations from mean. Violent arrests: rate of violent crime arrests per 1,000 people, deviations from mean. Officers employed: rate of police officers employed per 1,000 people, deviations from mean. Officers assaulted: rate of police officers assaulted per 1,000 people, deviations from mean. Drug arrests: rate of drug crime arrests per 1,000 people, deviations from mean. High school: share of population with high school diploma. House values: log median single family house value. Married: log of population that is married. All variables are averages of observations across the period 1978 to 2014. C.region FE: Census region fixed effects. Standard errors clustered on city in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$