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Financial opportunities: the relationship between neighborhood characteristics and intergenerational income mobility between counties

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Abstract

There is an emerging consensus in recent research that the neighbourhood in which an individual grows up in, has a substantial effect on the prospects of that individual's intergenerational income mobility. This paper researches the influence of neighborhood statistics (which includes rate of college degrees, violent crime rates, income inequality, high poverty areas and family structure) on the average intergenerational income mobility in a county with data from the United States. A beta regression with a log link function is employed to examine this relationship. We find that the rate of college degrees in counties is positively associated with intergenerational income mobility and that the rate of single-parent household in counties and the rate of poverty in counties is negatively associated with intergenerational income mobility. The effects of neighborhood characteristics on county level on intergenerational income mobility have been found in real life, in a non-experimental setting, where other externalities exist. Therefore, this research provides a practical foundation for further research. As county characteristics may rub off on the intergenerational financial opportunities of children, the government should invest extra in underprivileged counties.

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1 Introduction

Intergenerational income mobility is defined as the degree to which an individual's position in the income distribution differs to that of their parents. Historically, intergenerational income mobility is an extensively researched topic. It is used as a socioeconomic measure for the extent to which society provides equal chances to future generations. For instance, individuals, whose parents were below the 25th income percentile, that perform better than their parents are labelled as upward income mobility. This demonstrates to what extent individuals born in a relatively financially weak family are able to move up to a better financial situation in adulthood (Chetty, Friedman, Hendren, Jones, & Porter, 2018).

There is an emerging consensus in recent research that the neighbourhood in which an individual grows up in, has a substantial effect on the prospects of that individual's intergenerational income mobility. In the "moving to opportunity" experiment, randomly selected families in high-poverty neighbourhoods were offered housing vouchers that allowed them to move to lower-poverty neighbourhoods. Chetty, Hendren, and Katz (2016) found that the treatment effects were significant: children whose families moved to lower-poverty neighbourhoods at the age of 13 or younger achieved an annual income that was on average 31% higher than that of the control group in their mid-twenties. This could be attributed to the significantly higher college attendance rate amongst these individuals. These findings are corroborated by a quasi-experimental study of 7 million families in the US, which concluded that outcomes of individuals whose families moved to lower-poverty neighbourhoods improved linearly with the amount of time spend growing up in that neighbourhood (Chetty & Hendren, 2018). In another study, individuals, whose families were forced to move to lower-poverty neighbourhoods as a result of public housing demolitions, were found to be more likely to be employed and also to earn higher incomes in young adulthood, as compared to individuals that did not move (Chyn, 2018). Related studies by Deutscher (2020), Laliberté (2021) and Nakamura, Sigurdsson, and Steinsson (2016) on the relations between neighbourhood statistics and an individual's outcome have reached similar conclusions.

The positive relations between growing up in lower-poverty neighbourhoods and achieving more favourable outcomes in adulthood could be explained by theory. It is suggested that

the relatively affluent adults in lower-poverty neighbourhoods serve as role models, shaping the norms and social identity of the children that they interact with (Wilson, 2012). Moreover, the exposure to higher-income peers and adults in the area may provide job-finding opportunities and networks (Chyn, 2018). In addition, changes in the quality of schooling could significantly impact an individual's long-run labor market outcomes. Chetty et al. (2011) found that smaller class sizes, more experienced teachers and other indicators of class quality positively impacted future earnings. However, in the "moving to opportunity" experiment little changes in quality of school were found, even though families moved to significantly lower-poverty neighbourhoods. Therefore, the effects of changes in quality of education could only be a valid explanation for upward intergenerational income mobility when there exists a one-to-one relation between higher quality of education and the lower-poverty neighbourhood.

While previous literature has established a strong scientific and theoretical foundation for the effects of neighbourhood characteristics on the prospects of an individual's intergenerational income mobility, the practical foundation is still lacking, leaving a gap in the literature. The majority of research on the topic is built on an experimental set-up. The "moving to opportunity" experiment offered housing vouchers, allowing families to move from high-poverty to lower-poverty neighbourhoods, while another study focused on families that were forced out of their homes due to public housing demolitions. These situations provide natural experiments in which the effects of living in lower-poverty neighbourhoods can be isolated and exposed. The question remains, however, whether these effects can be found in real life, in a non-experimental setting, where other externalities exist. This would have to be researched with observational data. Therefore, the following research question is raised:

How can neighborhood statistics obtained from observational data help explain intergenerational income mobility on county level?

Answering this question is important as it sketches a more realistic image of the relationship between neighbourhood statistics and intergenerational income mobility, based on which policy makers can improve economic opportunity by identifying and personalizing policies to target underprivileged groups and redistribute economic opportunity more equally. Especially people from the less fortunate layers of society can benefit from this. Moreover,

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this paper contributes to the existing understanding on how neighborhoods characteristics could be used to explain an individual's relative financial outcome later in life. This paper researches these characteristics by using data from American individuals born between 1978 and 1983. A beta regression model is employed to determine the relations between intergenerational income mobility and the neighborhood characteristics.

The remainder of this paper is structured as follows. Section 2 Literature and hypotheses describes the existing literature, forms hypotheses based on the literature to help answer the research question and conceptualises the neighborhoods characteristics. Section 3 Data describes the source of the data, the variables, transformations to the the data and provides an exploratory and descriptive analysis. Section 4 Methodology describes the method this paper uses, why this method is used and shows the mathematical theory behind the method. Section 5 Analysis and results describes how the final model is chosen, tests the fit of the model to the data, presents the results of the analysis and provides answers to the hypotheses. Section 6 Discussion gives a further interpretation and explanation of the results, describes the limitations of this research and provides suggestions for future research. Section 7 Conclusion provides the answer to the research question.

2 Literature and hypotheses

The concern of social scientists about the extent to which income status is transmitted from one generation to the next, stems from the belief that transmittable income over generations violates equal opportunities. Adult economic status is generally positively correlated with the parental economic status (Jencks & Tach, 2006). This correlation is not necessarily a good indicator of the extent of equal opportunity in society. Unequal opportunities depend on the degree to which society minimize obstacles to economic success that can be altered to a certain extent, such as parental neglect, unjust distribution of quality of teachers and neighborhoods with high crime rates. However, equal opportunities does not mean absolute equal opportunities. Hard work, skill and intelligence should still be rewarded. People tend to believe income inequality is more acceptable if income mobility is high in society (Andrews & Leigh, 2009). Further evidence from Jencks and Tach (2006) finds that this believe of in-

come inequality being more acceptable if there is also high income mobility society is shared worldwide. In 1991 almost all adults in West-Germany, the United States, Britain and Japan agreed with the statement 'It's fair if people have more money and wealth, but only if there are equal opportunities" (Jencks & Tach, 2006). It is important for society as well as science that this intergenerational income mobility can be quantified and conceptualised. It is a measure to what extent society provides financial opportunities and it helps science understand what the determinants are of equal opportunities.

The determinants of intergenerational income mobility seem to vary per country. Evidence from South Africa suggests that demographic changes such as fertility and mortality rate and employment changes such as a volatile labour market account for most of the income mobility (Woolard & Klasen, 2005). Evidence from Korea suggests that demographic changes such as illness, family breakdown and aging are the most important determinants for income mobility (Oh & Choi, 2018). An explanation is that each country has its own unique characteristics and problems, therefore the suggestion is that determinants of income mobility also depend on the country itself, which makes country comparisons difficult. However, there are effects that seem to be true globally. For example, investment in education is found to be an important driver of income mobility among multiple researches (Yang & Qiu, 2016; Restuccia & Urrutia, 2004), which will be further described in the next section. Generally, industrialised and developed countries have lower mobility. In addition, the bottom quantile and the top quantile of the income distribution have lower mobility compared to the quantiles in between (Woolard & Klasen, 2005; Oh & Choi, 2018). The suggestion is that extremely poor people and extremely rich people are in extreme financial positions, which limits the amount of influence a person has on their financial position compared to people between the bottom and top quantile. The next part describes how intergenerational income mobility is measured.

In economic papers, intergenerational income mobility is generally estimated by the correlation between the income of the parents and their offspring: the intergenerational correlation of earnings (Cervini-Plá, 2009). It is referred as perfect mobility if this correlation is 0 and it is referred as perfect immobile if this correlation is 1. A typical regression would look like this:

$$\ln Y_{sons} = \rho \ln Y_{father} + \epsilon_{sons} \tag{1}$$

Where y represents the income and ρ represents the earning elasticity (Couch & Lillard, 1998). This paper dates back from 1998, nowadays, a more appropriate definition would be parent and children instead of sons and father. Following the approach from Chetty, Hendren, Kline, and Saez (2014), this paper uses the mean rank of income of children whose parents are at the 25th percentile of the parent income distribution. This makes comparisons between different generations more fair, as inflation and higher average wages do not influence the measure compared to measuring absolute income differences between generations as intergenerational income mobility.

Continuing, there is an emerging consensus in recent research that the neighbourhood in which an individual grows up in, has a substantial effect on the prospects of that individual's intergenerational income mobility (Chetty et al., 2016; Chetty & Hendren, 2018; Deutscher, 2020; Chyn, 2018). Children have no influence on the neighborhood they grow up in, therefore opportunities are unjust divided among neighborhoods if neighborhoods affect your ability to transcend the income classes. For example, the amount of experience a kindergarten teacher has is positively correlated with income in adulthood (Chetty et al., 2011). Therefore, children who grow up in neighborhoods with schools with more experienced teachers have more opportunities to transcend the income classes.

Furthermore, the environment a child grows up in may encourage or discourage you to outperform your parents financially. Children's norms and social identity are partly formed by the neighborhood they grow up in. The people in the neighborhoods serve as role models (Wilson, 2012). Neighborhoods can be characterised by a range of aspects, amongst others are education, income inequality at neighborhood level, high-poverty areas, violent crime rate and family structure, which will be described below.

2.1 Education

Early academic literature has shown that education is one of the most important determinants of income, from evidence dating back to 1974 (Mincer, 1974). Education is seen as an investment in human capital. The rate of return on higher education is higher than the rate of return on lower compulsory education. Furthermore, this return remains comparatively high despite the increase of higher educated people. Therefore, those who are more

educated earn higher wages on average (Wolla & Sullivan, 2017). Especially early investment in education is an important determinant of income mobility. The financial gap between the wealthiest and poorest families' children is rather due to early investment in education than intelligence. This gap results in greater income inequality and less intergenerational income mobility than differences in innate ability (Yang & Qiu, 2016). These results are in line with results from Restuccia and Urrutia (2004), who estimated that parent's early investments in education explains approximately 50% of intergenerational income mobility.

One's education evidently influences one's ability to move up the income ladder. However, this paper researches the effects of exposure to an environment that is educated and not the direct effects of education. Therefore, the effect of exposing children to different rates of college degrees while growing up in counties is researched. The theory of Wilson (2012) states that relatively affluent adults in lower-poverty neighbourhoods serve as role models, shaping the norms and social identity of the children that they interact with. Therefore, neighborhoods with relatively highly educated people could encourage children to academically outperform children growing up in neighborhoods with relatively poorly educated people. This difference in education is then translated into upward income mobility. Moreover, the exposure to high-income adults in the area may provide job-finding opportunities for the parents and a social network, which the children can leverage from later in life. As a result, parents are more likely to work and invest in their children educational development. Furthermore, children can leverage from this network and are more likely to find a job as well, further increasing their upward income mobility (Chyn, 2018).

Education is an important determinant of earnings (Wolla & Sullivan, 2017). Therefore, investments in the children's educational development influence their intergenerational income mobility (Yang & Qiu, 2016). Especially, early investment in education is important for explaining intergenerational income mobility (Restuccia & Urrutia, 2004). Exposing these children to areas with high-income adults may positively influence children's intergenerational income mobility by encouraging children to do well at school and by providing job-finding opportunities and a network for their parents and themselves (Wilson, 2012; Chyn, 2018). Based on the mentioned studies the following hypothesis is formed:

Hypothesis 1: The rate of college degrees in a county is positively associated with
intergenerational income mobility

2.2   Income inequality among neighborhoods

Income inequality and intergenerational income mobility are by definition related to each
other. Income inequality is the difference in income distribution among families within the
same cohort and intergenerational income is the difference in income distribution among
families between generations (Yang & Qiu, 2016). Intergenerational income mobility has
decreased for children born in 1950 compared to 1984 in America. Only 50% of the children
in 1984 are doing better than their parents compared to 90% of the children born in 1950.
This decline in income mobility is suggested to be driven by unequal distribution of economic
growth in recent decades (Chetty et al., 2017). This finding is also supported by Corak (2013)
and Björklund, Jäntti, et al. (2009), who find that countries with more unequal distribution of
income also show less income mobility than countries with relatively more equal distribution
of income. Growth is an important driver for income mobility, but it requires a broad growth
across the income distribution (Chetty et al., 2017).

There is also evidence from America that income inequality among states during youth
does not affect income mobility from Bloome (2015). This lack of association between income
inequality and mobility may derive from offsetting effects. These are effects that counterbal-
ance the reduced opportunities children face due to income inequality. For example, income
inequality leads to unequal private investment in children's education, which could be coun-
terbalanced by policies such as a redistributive public investment in children's education,
where less economically fortunate children relatively gain more from the system.

While Bloome (2015) did not find an association between income inequality and income
mobility, based on the offsetting effects discussed and studies from Chetty et al. (2017),
Corak (2013) and Björklund et al. (2009) we still expect that income inequality leads to
lower intergenerational income mobility.

Hypothesis 2: The income inequality in a county is negatively associated with
intergenerational income mobility

2.3 High poverty areas

Another aspect of neighborhoods that might affect intergenerational income mobility is poverty. There is an experiment called the Moving To Opportunity (MTO) (Chetty et al., 2016). Moving children from higher-poverty to lower-poverty areas before the age of 13 increases college attendance, earnings in adulthood and performance on standardized tests (Chetty et al., 2016). This is mainly attributed to having different role models while growing up and more opportunities and a stronger network to leverage from. This is the same social mechanic as described in section 2.1 Education. Relatively affluent adults in lower-poverty neighborhoods play a positive role in shaping the norms and social identity of the children they interact with (Wilson, 2012). As a result, these children in lower-poverty areas may perform better than their peers who grew up in high-poverty areas with worse financial role models. In addition, lower-poverty areas may provide better job opportunities and a network to the parents and children who can financially leverage from that (Chyn, 2018).

Initially, the MTO influences girls more positively and strongly than boys in terms of behavioural problems (e.g. crime) and academic performance. However, in the long run there is not a significant difference between genders in college attainment and earnings due to the MTO effects. Interestingly, moving as adolescents has a slightly negative impact on income in adulthood (Chetty et al., 2016). The authors are not sure why this is the case, but perhaps personalities are already more shaped and rigid in adolescence ($>$13 years) while children in childhood ($<$ 13 years) are more moldable to the environment they grow up in. Therefore, it also matters at which age a child grows up in a lover- or higher-poverty area.

High-poverty areas may discourage children to do better than their parents, because the children become accustomed to the lower living standards in those neighborhood and their personalities are influenced negatively by the role-models in those neighborhoods. This negative effect of role-models on the development of of children is based on Wilson (2012). Furthermore, growing up in high poverty-areas may provide less job-finding opportunities and networks compared to lower poverty-areas reducing intergenerational income mobility (Chyn, 2018). Based on the mentioned studies the following hypothesis is formed:

Hypothesis 3: The poverty rate in a county is negatively associated with intergenerational

2.4 Violent crime

Neighborhoods can also differ in the degree of crime, specifically violent crime. These typically harsh environments with features such as high incarceration and violent crime rates are linked to instability of neighborhoods and families and blunting of cognitive development (Manduca & Sampson, 2019). Hazards such as incarceration and violence are negatively associated with intergenerational income mobility in neighborhoods and positively with adult incarceration rates (Manduca & Sampson, 2019). This is also supported by Sharkey and Torrats-Espinosa (2017). The researchers find evidence that the level of violent crimes has a causal effect on the intergenerational income mobility on individual level, using data from children born at the 25th percentile of the income distribution. One explanation they provide is that violent crime rates are positively associated with high school drop out rates, which weakens the position of children in the labor market in adulthood and decreases their opportunities in adulthood.

Furthermore, indirect evidence for the association between violent crimes and intergenerational income mobility comes from Dennison (2019). Dennison (2019) finds that upward educational mobility is negatively associated with violent crimes. As described in section 2.1 Education, violent crimes can therefore also be linked with intergenerational income mobility through education. If people are able to perform better academically than their parents due to lower violent crime rates while growing up, then on average they must have better chances at upward income mobility too. Based on the mentioned studies the following hypothesis is formed:

Hypothesis 4: The violent crime rate in a county is negatively associated with intergenerational income mobility

2.5 Family structure

There is a trend of increase in children growing up with one parent in the Western world. The share of single parent families in Europe rose from 10 to 21 % between 1980 and

2008 (Jokinen & Kuronen, 2011). Bad socioeconomic outcomes and poverty are more much common in these single-parent households than in two-parent households (Brodolini, 2007). Family structure could also play an important role in intergenerational income mobility.

This paper distinguishes two cases: children growing up in a single-parent household and children growing up in a two-parent household. Chetty et al. (2014) finds a negative correlation between single-parent households and upward income mobility on the individual level as well as on the commuting zone level (geographical area). This means that not only children from divorced parents experience lower income mobility, but also children with married parents who live in a commuting zone with a relatively high rate of divorced parents compared to children with married parents from areas with low rates of one-parent families (Chetty et al., 2014). In addition, Bloome (2017) finds that children born with only one parent have increased downwards income mobility. Children may perform worse at school in one-parent families than in two-parent families due to less resources available to invest in education. This can result in worse job opportunities and thus a lower income in adulthood.

The findings from Chetty et al. (2014) are especially important, because they suggest that the effect of a one-parent household is not only on the individual level but also on the aggregate level. The observations in this paper are counties, therefore per definition we are looking at effects on aggregate level. Furthermore, one-parent households have less capital to invest in education than two-parent households and this could negatively affect upward income mobility. This mechanism between investment in education and intergenerational income mobility is described in section 2.1 Education. Based on the mentioned studies the following hypothesis is formed:

Hypothesis 5: The single-parent rate in a county is negatively associated with intergenerational income mobility

To summarize, neighborhood statistics such as educational attainment, family structure, crime rates and poverty may influence the extent to which children outearn their parents.

3 Data

This section first describes where the data is obtained from, how the data is collected, what the contents of the data are and on what level the data is measured. Secondly, the variables used in the analysis are described and explained how they are defined. Finally, the transformations of the data and a descriptive analysis of the data are shown.

3.1 The Opportunity Atlas

The Opportunity Atlas (OA) is a collection of data sets constructed and published by Chetty et al. (2018). It is a combination of three anonymous sources from the United States Census Bureau. That is the 2000 and 2010 Decennial Census short form, the 2000 Decennial Census long form and federal income tax returns for 1989, 1994, 1995, and 1998-2015. The Opportunity Atlas contains data on over 20 million anonymous Americans, who are randomly selected and have been followed from their childhood to their mid thirties. The Opportunity Atlas contains many variables and the data is divided into geographical areas: commuting zones, counties and Census tracts. We are interested in the variables that are measured on county level with at least 10000 residents. The variables on county level selected for this study are: intergenerational income mobility, mean household income, median household income, share of individuals below the poverty line, share of individuals with a college degree and the number of single parent families, all per county from the year 2000. The individuals in the OA were born between 1978 and 1983.

Crime rates for the counties are not recorded in the OA. Therefore, these were collected from the Uniform Crime Reporting (UCR) Program (FBI, 2000) and subsequently merged with the Opportunity Atlas. The UCR Program is part of the Federal Bureau of Investigation of the United States. Data of this program traces back to as early as 1995. Only counties for which a match between the OA and UCR Program was found are included in the analysis. This amounts to 2092 counties. The variables described in the subsection Variables are all on county level.

3.2 Variables

A shorter description of these variables can also be found in Appendix A.

3.2.1 Intergenerational income mobility

The dependent variable of interest is the mean rank per county of the income percentiles of individuals born in families at the 25th percentile of the income distribution, and is also denoted by *igm*. An individual therefore outperforms his or her parents when their rank is at least 0.25. The observations used in this paper are the mean rank per county of percentiles in the national distribution of household income in 2014-2015 for children born between 1978 and 1983 with parents at the 25th percentile of the national income distribution. Only counties with 10000 residents or more are included in the data set.

3.2.2 College, poor areas and family structure

The other independent variables are taken directly from the OA. These are: *fraction_college*, *poor_share* and *single_parent*. The first captures the number of individuals aged 25 or older with a bachelor's degree, master's degree, professional school degree or doctorate degree, divided by the total number of individuals aged 25 or older, for each county in the year 2000. The second captures the share of individuals in a county living below the federal poverty line in the year 2000. The variable *single_parent* captures the share of single parent families with children under 18 years, relative to the total number of families with children under 18 years, in the year 2000.

3.2.3 Income inequality

income_inequality is one of the independent variables used in this paper. To derive a measure for income inequality, we consider the mean household income and the median household income. Income inequality concerns the gap between different household incomes, and is therefore large when we observe extremely high and extremely low household incomes in a county. Since the mean is affected by such extreme observations and the median is not, the difference between the two is small when there is little income inequality, and large

when there is much income inequality. However, simply considering the absolute difference between the mean and median household income does not suffice. This paper employs cross-sectional data from various counties, for which the absolute difference in mean and median household income may differ in scale. To ensure that these differences in scale do not bias the results, the absolute difference between the mean and median household income is re-scaled by dividing by the median household income. To summarize, the paper measures income inequality as the difference between the mean household income and the median household income divided by the median household income. Both the mean and median household incomes per county are taken from the OA from the year 2000.

3.2.4 Violent crime

The final independent variable is $crime\_rate$, which measures the number of violent crimes per 1000 inhabitants in the year 2000 for each county. This data is obtained from the UCR Program. According to the UCR program's definition, violent crime is the act of force or threat of force. The crimes considered for this variable are murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault.

3.2.5 Races

This paper controls for four races: Black, White, Hispanic and Asian. Therefore, the control variables $black$, $white$, $hispanic$ and $asian$ are included in the analysis. These variables are also taken directly from the Opportunity Atlas and capture the share of Black, White, Hispanic or Asian individuals in each county for the year 2000. Further typically used control variables for researching income mobility are teenage birth rates, quality of teachers, social capital (e.g. social network, communities local areas) and high school drop out rates (Chetty et al., 2014, 2018). This paper does not control for those variables, as they were not directly available from the OA (on county level).

3.3   Descriptive statistics

The total amount of observations in the data are 2092 observations, which includes 9 explanatory variables and 1 variable of interest. There are no missing values. However, there is an outlier in the data for the variable violent crime rate, see Figure 1. This outlier can perhaps can be due to a registration error. This observation is removed from the data set.
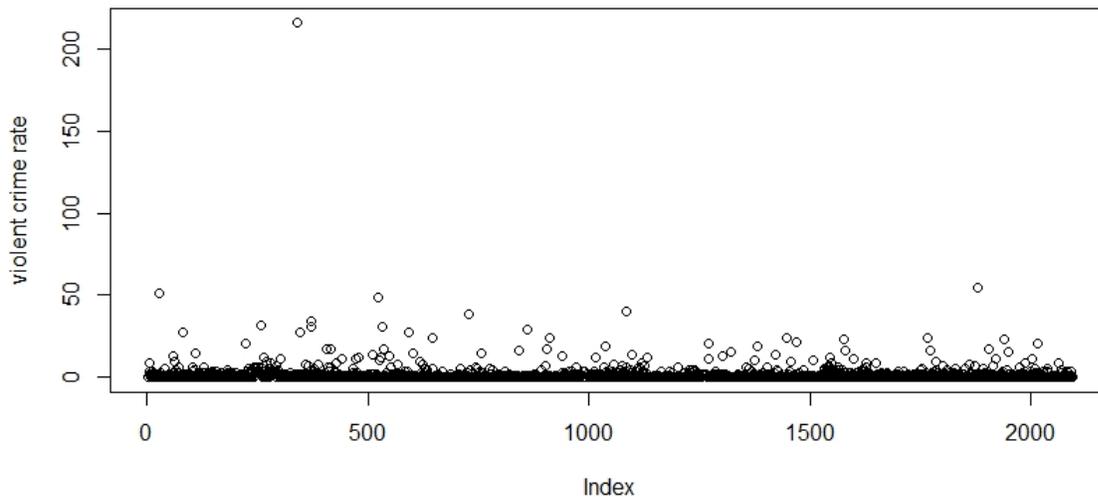

FIGURE 1: Scatter plot of violent crime rate

The minimum, mean and maximum values of the explanatory and variable of interest are given in Table 1. On average we see that the rate of college degrees is 17% in the counties. Interestingly, the maximum value of income inequality is 1.15, which is defined as the average household income minus the median household income divided by the median household income. Therefore, an income inequality value of 1 would mean that the average household income is twice as big as the median household income, which would indicate that there is a big difference between the bottom 50% earners and the top 50% earners. Furthermore, the average violent crime rate is only 1.68 per 1000 inhabitants per county. This number may be higher in reality, because in practice not all violent crimes committed are reported to the police.

TABLE 1: Descriptive statistics for the variables

Variable	Minimum	Mean	Maximum
fraction_college	0.05	0.17	0.56
poor_share	0.02	0.13	0.51
single_parent	0.10	0.26	0.60
income_inequality	0.04	0.33	1.15
crime_rate	0	1.68	54.50
igm	0.31	0.42	0.61

In Figure 2 we see the correlation plot for all the variables. The diagonal shows the correlation of the variables with itself, which is 1 of course. We notice that there is racial segregation between the counties. The share of White people in a county is negatively correlated with the share of Black people and the share of Hispanic people. Therefore, counties with relatively more White people also have relatively less Black and Hispanic people. According to the figure, the share of Black people is strongly negatively correlated with intergenerational income mobility and the share of White people is moderately positively correlated with intergenerational income mobility. Contrary, the share of Hispanic people is not correlated with intergenerational income mobility. The share of Asian people is not correlated with other races as well as intergenerational income mobility. Furthermore, there is a strong negative correlation between intergenerational income mobility and counties with relatively higher rates of single parents and higher rates of people living in poverty. It is logical that these two are correlated as you have less income as a single-parent household than as a two-parent household, hence the positive correlation between those two. However, we also see that income inequality is not correlated with intergenerational income mobility and that the fraction of people with college degrees is only moderately correlated with intergenerational income mobility.

Furthermore, the explanatory variables are correlated amongst themselves. For example, the rate of poverty in a county is moderately correlated with the rate of college degrees. There may be multicolinearity between the variables, which reduces the precision of the estimated coefficients and may cause coefficients to be wrongly insignificant. To test whether there is

multicolinearity, we use the variance inflation factor (VIF) (Akinwande, Dikko, Samson, et al., 2015). Generally speaking, a VIF of 1 means that the variables are not correlated with each other at all, a VIF between 2 and 5 would they are moderately correlated and a VIF of 5 or higher would mean the variables are highly correlated to each other. The VIFs are shown in Tables 2 and 3. The highest VIF among the explanatory variables is only 2.24. Therefore, there is strong evidence that there is no multicolinearity among the explanatory variables.
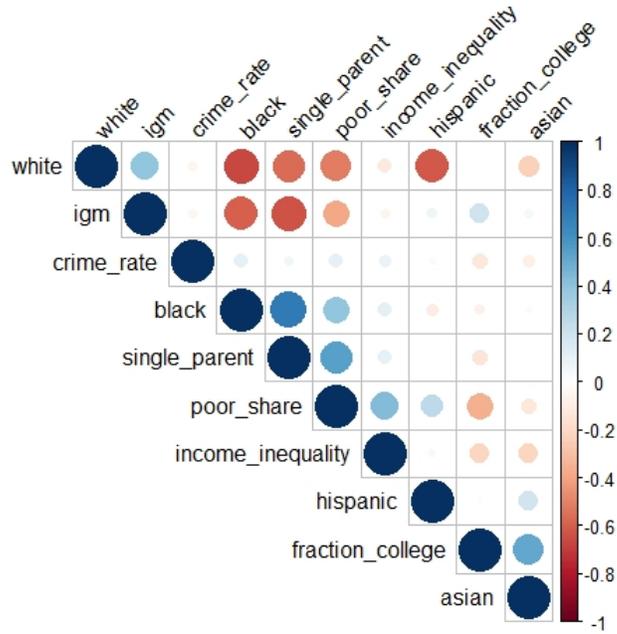

FIGURE 2: Correlation plot of all variables

Variable	$fraction\_college$	$poor\_share$	$white$	$hispanic$	$asian$
VIF	1.58	2.22	14.05	7.84	1.62

TABLE 2: Part 1 VIF for the variables

Variable	$single\_parent$	$income\_inequality$	$crime\_rate$	$black$
VIF	2.24	1.29	1.03	6.72

TABLE 3: Part 2 VIF for the variables

4 Methodology

This section starts with an introduction of beta regressions. Then the shortcomings and inappropriateness of OLS and logistic regression for this data set is highlighted. We continue with the mathematical details of the beta distribution and the beta regression. Finally, we describe the model we used in this paper.

4.1 Beta Regression

This paper employs a beta regression to study the association between intergenerational income mobility and neighbourhood statistics. The dependent variable, inter-generational income mobility measured by igm, is a continuous variable that is restricted on the interval (0,1), which makes a beta regression appropriate. The dependent variable is related to independent variables through a regression model. Beta regressions are suitable to model continuous dependent variables on the zero to one scale, excluding the endpoints (0.1). Furthermore, it is often proved useful in the case of long tails and heteroskedasticity (Migliorati, Di Brisco, & Ongaro, 2018).

Generalized linear models refer to a large class of models, which includes linear regression and logistic regression. Beta regression is similar to a generalized linear model (GLM), but the assumed distribution is not part of the exponential family but part of the beta distribution. The model contains three components: a systematic component, a random component and a link function. The systematic component concerns the linear predictor, containing the regressors and coefficients. The random component, modeled by an error term, takes the uncertainty in the model into account. The link function specifies the relationship between the systematic and the random component (Ferrari & Cribari-Neto, 2004).

4.2 Shortcomings of OLS and Logistic Regression

Regular Ordinary Least Squares (OLS) is inappropriate, because it does not take into account the restrictions on the dependent variable and may therefore generate fitted values that exceed the upper or lower bound. One way to work around this limitation of OLS is to transform the dependent variable to assume values between 0 and 1. However, this

approach has some drawbacks. For example, it complicates the interpretation of the model parameters in terms of the original response variable. Since the main objective of this paper is to reveal the associations between the dependent and independent variables, such a trait is undesirable. Another limitation of OLS is that it assumes a normal and therefore symmetric distribution for the dependent variable. Typically, proportions display asymmetry, such that the results from OLS can be misleading.

A logistic regression assumes the dependent variable to be either the value 0 or 1, which is a discrete method. However, intergenerational income mobility is a continues variable between 0 and 1, which makes logistic inappropriate. Contrary, a beta regression strictly requires that none of the dependent variable observations are 0 or 1.

Beta regression assumes that the response variable follows a beta distribution, which is more flexible than a normal distribution. It is this flexibility that encourages its empirical use in a wide range of applications (Johnson, Kotz, & Balakrishnan, 1995). Furthermore, Douma and Weedon (2019) encourages to use beta regression to analyse data with dependent variables that are expressed as percentages or fractions and provides examples of this technique used in the literature.

4.3 Mathematical details beta regression

The mathematical details of the distribution and beta regression in this section are based on Douma and Weedon (2019). The beta distribution uses parameters α and β such that the probability density function for a beta-distributed response variable y is defined as the following:

$$f(y|\alpha, \beta) = \frac{y^{\alpha-1}(1-y)^{\beta-1}}{B(\alpha, \beta)} \tag{2}$$

where

$$B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha + \beta)} \tag{3}$$

and $\Gamma(.)$ is the gamma function. The expectation and variance of the beta distribution are then as follows:

$$E[y] = \frac{\alpha}{\alpha + \beta} \tag{4}$$

and

$$var[y] = \frac{\alpha\beta}{(\alpha + \beta)^2(\alpha + \beta + 1)} \tag{5}$$

Usually for modelling data, μ and ϕ are used as alternative parameters for the beta distribution. This is done by setting $\mu = \frac{\alpha}{\alpha+\beta}$ and $\phi = \alpha + \beta$ such that:

$$E[y] = \mu \tag{6}$$

$$var[y] = \frac{\mu(1 - \mu)}{1 + \phi} \tag{7}$$

Then we have

$$y \sim Beta(\mu, \phi) \tag{8}$$

For fixed μ, the larger ϕ becomes the smaller the variance of y becomes as the denominator in equation 7 becomes bigger. Therefore, the parameter ϕ is known as the precision parameter. The beta regression is then defined as:

$$g(\mu_i) = x_i^T \beta = \eta_i \tag{9}$$

here $\beta = (\beta_1, ..., \beta_k)^T$ is is a vector of k unknown regression coefficients, $x_i = (x_{i1}, ..., x_{ik})^T$ is a vector of k independent variables and η_i is the linear predictor. Here μ_i is the expected value of y given the explanatory variables x, also denoted by $\hat{y}$. The link function is specified by $g(\mu_i)$, which is strictly increasing and twice differentiable. The most used link function is the logit function, because of its interpretability (Douma & Weedon, 2019):

$$logit(\mu) = g(\mu) = ln(\frac{\mu}{1 - \mu}) \tag{10}$$

Finally, we need to take the inverse of the logit function to get estimates from beta that are interpretable on the (0,1) scale. This is done by:

$$\hat{y} = g(\mu_i)^-1 = \frac{e^\eta}{1 + e^\eta} \tag{11}$$

where η is $x_i^T\beta$.

4.4 The model

The link function affects how well the model fits the data and the interpretability of the regression coefficients. Therefore, we try to get the model that fits the data best but also take into consideration interpretability. Generally speaking, the regression coefficients of loglog (double log of y) are not interpretable. We use the Akaike Information Criterion (AIC) (Cavanaugh & Neath, 2019) and Bayesian Information Criterion (BIC) (Neath & Cavanaugh, 2012) to decide which link function fits the data best. A lower AIC and BIC means that the model fits the data better.

After we find the appropriate link function, we set up the beta regression with the link function:

$$g(\hat{igm}\_i) = \beta_0 + \beta_1 \cdot income\_inequality + \beta_4 \cdot fraction\_college + \beta_5 \cdot poor\_share + \beta_6 \cdot single\_parent$$
$$+ \beta_7 \cdot crime\_rate + c_1 \cdot share\_black + c_2 \cdot share\_hispanic + c_3 \cdot share\_asian$$

The coefficients of the explanatory and control variables are denoted as β_i and C_i. Then this link function is inversely transformed by taking the inverse of the link function to get the appropriate beta regression coefficients and prediction $\hat{y}$.

$$\hat{igm}_i = g^-1(\beta_0 + \beta_1 \cdot income\_inequality + \beta_4 \cdot fraction\_college + \beta_5 \cdot poor\_share + \beta_6 \cdot single\_parent$$
$$+ \beta_7 \cdot crime\_rate + c_1 \cdot share\_black + c_2 \cdot share\_hispanic + c_3 \cdot share\_asian) \quad (12)$$

Here g^-1 is the inverse of the link function.

5 Analysis and Results

This section presents the analysis and results of the beta regression discussed in section 4 Methodology . This starts with the choice of the link function. Then the fit of the model is examined. Finally, the results are interpreted.

5.1 Link function and fit of model

This paper uses four different link functions to construct 4 different beta regressions. These are the logit, loglog, log and probit link function. The AIC and BIC scores for each

model are shown in Table 4. The differences in the scores are relatively small, which indicates that the difference in fit between the models is also relatively small. The beta regression with the log link function has the lowest AIC as well as the lowest BIC. Therefore, this model fits the data the best and is used as the final model in this paper.

TABLE 4: AIC and BIC values for models with different link functions

Link function	AIC	BIC	degrees of freedom
logit	-8085	-8023	11
loglog	-8048	-7986	11
log	-8135	-8073	11
probit	-8077	-8015	11

Next, the fit of the model is examined. Figure 3 shows the predicted vs observed values. The dashed line gives the predictions for the corresponding observed values. The figure shows that the regression fits the observed values decently until a value of 0.5 of intergenerational income mobility. The prediction of intergenerational income mobility beyond 0.5 are not captured well by our model. It seems that for high positive observations the prediction errors are relatively high. This is confirmed by Figure 4. Figure 4 shows the QQ plot. The variance of the residuals at the higher quantiles increases. Therefore, it seems that the residuals are right skewed. In conclusion, the model is able to capture the relationship decently, but at greater levels of intergenerational income mobility the fit of our model to the data decreases significantly.
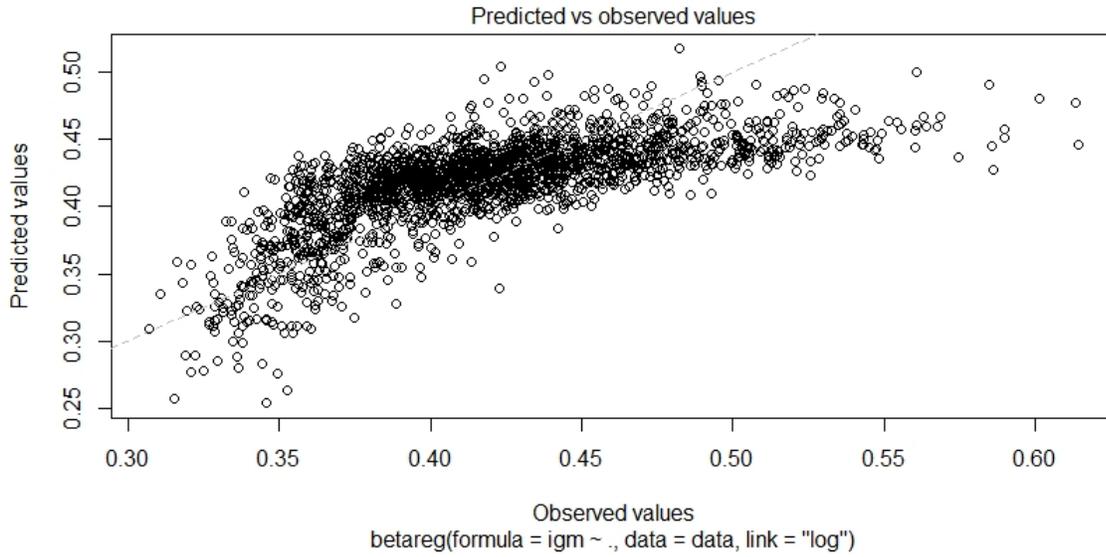
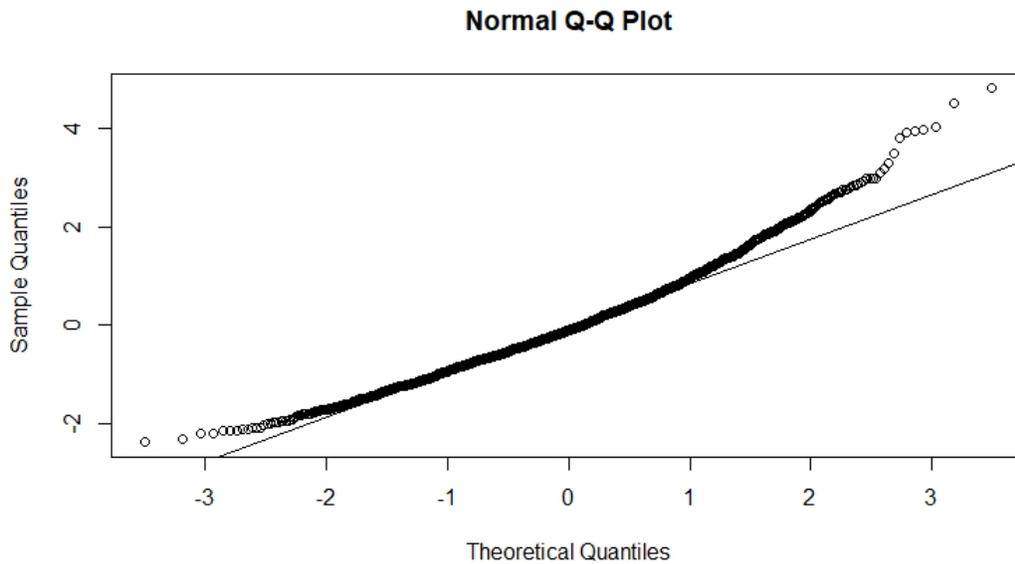FIGURE 3: Predicted vs observed values

FIGURE 4: Residuals against the quantiles of intergenerational income mobility

5.2 Model results

This section shows the results of the model. The hypotheses established in section 2 Literature and Hypothesis are answered by using Table 5. Table 5 shows the regression coef-

ficients of the beta regression with a log link function. The interpretation of the coefficients is the same as in a regression where the dependent variable is log-transformed. Thus, the effect of the coefficients are equal to $(e^{\beta} - 1)\%$. Most variables are percentual variables between 0 and 1, therefore it is more convenient to look at effects of x on y in terms of an increase of 0.1 (=10%) in the fractional explanatory variables instead of 1 (=100%).

TABLE 5: Model results from beta regression with log link function

Coefficients	Estimate	Std. Error	Z-value	Pr(>|z|)	Significance
Constant	-0.60	0.04	-13.44	2e-16	***
fraction_college	0.19	0.03	6.88	5.87e-12	***
poor_share	-0.11	0.05	-2.33	0.02	*
black	-0.37	0.04	-9.13	2e-16	***
white	-0.07	0.04	-1.76	0.08	.
hispanic	-0.02	0.04	-0.42	0.68	
asian	-0.27	0.16	-1.64	0.10	
single_parent	-0.80	0.05	-16.43	2e-16	***
income_inequality	0.04	0.02	2.39	0.02	*
crime_rate	0.00	0.00	1.38	0.17	

Significance codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Hypothesis 1: The rate of college degrees in a county is positively associated with intergenerational income mobility

We find that the relationship between the fraction of college degrees and intergenerational income mobility is significant on a 0.1 % level and has a positive sign. A 10% increase in the fraction of college degrees in a county is associated with an average increase of 2.1% in the intergenerational income mobility in a county for people born at the 25th income percentile, ceterus paribus. We find a positive association between the rate of college degrees in a county and intergenerational income mobility, therefore hypothesis 1 holds.

Hypothesis 2: The income inequality in a county is negatively associated with intergenerational income mobility

We find that the relationship between income inequality and intergenerational income mobility is significant on a 5% significance level and has a positive sign. A 0.1 increase in income inequality in a county is associated with an average increase of 0.4% in the intergenerational income mobility in a county for people born at the 25th income percentile, ceterus paribus. We do not find a negative association between income inequality in a county and intergenerational income mobility, therefore hypothesis 2 does not hold.

Hypothesis 3: The poverty rate in a county is negatively associated with intergenerational income mobility

We find that the relationship between the share of people living in poverty and intergenerational income mobility is significant on a 5% level and has a negative sign. A 10% increase in the share of people living in poverty in a county is associated with an average decrease of 1% in intergenerational income mobility in a county for people born at the 25th income percentile, ceterus paribus. We find a negative association between the poverty rate in a county and intergenerational income mobility, therefore hypothesis 3 holds.

Hypothesis 4: The violent crime rate in a county is negatively associated with intergenerational income mobility

We find that the relationship between violent crime rates and intergenerational income mobility is not significant on a 10% level. Therefore, we can not interpret the coefficient of the violent crime rates. We find no association between violent crime rates in a county and intergenerational income mobility, therefore hypothesis 4 does not hold.

Hypothesis 5: The single-parent rate in a county is negatively associated with intergenerational income mobility

We find that the relationship between the share of single-parent households and intergenerational income mobility is significant on the 0.1% level and has a negative sign. A 10% increase in the share of single-parent households in a county is associated with a decrease of 5.5% in the intergenerational income mobility in a county for people born at the 25th income percentile, ceterus paribus. We find a significant negative association between the share single-parent households and intergenerational income mobility, therefore hypothesis 5 holds.

6 Discussion

This section describes how the results can be interpreted and what the implications of these findings are. Next, the limitations of this study are described. Finally, this paper provides recommendations fur further research.

6.1 Interpretation and implications of results

The results indicate that there is a significant association between neighborhood characteristics and intergenerational income mobility on county level.

> Hypothesis 1: The rate of college degrees in a county is positively associated with
> intergenerational income mobility

Wolla and Sullivan (2017) stated that those who are more educated earn higher wages on average. We find a positive and significant relationship between the rate of college degrees in a county and intergenerational income mobility, which supports hypothesis 1 and is expected based on the literature in section 2. It seems that the positive effects of educational role models rubs off on the next generation on county level: counties with historically higher rates of college degrees also show to have a higher average intergenerational income mobility. This finding can be explained by the role model function the adults play while growing up as a child (Wilson, 2012). The suggestion is that children's norms and values are shaped accordingly to the positive qualities the neighborhoods exposes them to, which enhances their ability to outperform their parents financially. Moreover, the exposure to high-income adults in the area may provide job-finding opportunities for the parents and a social network, which the children can leverage from later in life. As a result, parents are more likely to work and invest in their children educational development. Furthermore, children can leverage from this network and are more likely to find a job as well, further increasing their upward income mobility (Chyn, 2018).

> Hypothesis 2: The income inequality in a county is negatively associated with
> intergenerational income mobility

Chetty et al. (2017), Corak (2013) and Björklund et al. (2009) find that income inequality decreases intergenerational income mobility on country level. Bloome (2015) finds no association between between income inequality and income mobility on state level. We find a small positive effect between income inequality and intergenerational mobility on county level, which was expected to be negative. An explanation for finding a small positive effect are offsetting effects such as policies taken by the government that reduce the difference in opportunities, because there is income inequality (Bloome, 2015). Therefore, this coefficient could be biased upwards. Another explanation is that income inequality is not captured well enough by the conceptualisation of income inequality this paper used, where the difference between the mean and the median household income divided by the median household income was taken. We find a positive and significant relationship between the income inequality in a county and intergenerational income mobility, which does not support hypothesis 2 and is unexpected based on the mentioned literature.

Hypothesis 3: The poverty rate in a county is negatively associated with intergenerational income mobility

Relatively affluent adults in lower-poverty neighborhoods play a positive role in shaping the norms and social identity of the children they interact with (Wilson, 2012). As a result, these children in lower-poverty areas may perform better than their peers who grew up in high-poverty areas with worse financial role models. Furthermore, growing up in high poverty-areas may provide less job-finding opportunities and networks compared to lower poverty-areas reducing intergenerational income mobility (Chyn, 2018). The results show a negative effect of the share of people living in poverty on intergenerational income mobility: counties with a historically high level of poverty seem to rub off some negative effects on the next generation on county level. We find a negative and significant relationship between the poverty rate in a county and intergenerational income mobility, which supports hypothesis 3 and is expected based on the mentioned literature.

Hypothesis 4: The violent crime rate in a county is negatively associated with intergenerational income mobility

Sharkey and Torrats-Espinosa (2017) finds evidence that the level of violent crimes in a

county has a causal effect on intergenerational income mobility on individual level, using data from children born at the 25th income percentile. One explanation they provide is that violent crime rates are positively associated with high school drop out rates, which significantly weakens the position of children in the labor market in adulthood and decreases their opportunities in adulthood. We do not find this effect on county level. A possible explanation for our finding may be that people are more likely to move to a different county after experiencing high violent crime rates in their neighborhood while growing up. As a result, the effects of violent crime rates on the average intergenerational income mobility is not a fair comparison between counties and therefore we may not find an effect on county level. We do not find a significant relationship between the violent crime rate in a county and intergenerational income mobility, which does not support hypothesis 4 and is unexpected based on the mentioned literature.

Hypothesis 5: The single-parent rate in a county is negatively associated with intergenerational income mobility

Chetty et al. (2014) finds a negative correlation between single-parent households and upward income mobility on the individual level as well as on the commuting zone level (geographical area). Bloome (2017) finds that children born with only one parent have increased downwards income mobility. We find a strong negative relationship between the share of single-parent households and intergenerational income mobility: counties with a historically high rate of single parents have lower rates of intergenerational income mobility and therefore also less opportunities to move up the economic ladder. This outcome was expected based on the literature in section 2. This can be explained by the fact that single-parent households generally have less money to invest in their children's education, while especially parent's early investments in education explains approximately 50% of intergenerational income mobility (Restuccia & Urrutia, 2004). This can result in worse job opportunities and thus a lower income in adulthood.

6.2 Limitations

The results of this paper should be carefully interpreted and no causal effects can be derived from the analysis in this paper due to three reasons. One, this paper used observational data. Two, there is omitted variable bias. Three, the one to one relationship between the effects of the characteristics of a county and its future intergenerational income mobility is hard to establish. Reason one and two coincide, observational data are subject to biases from selection and measurement and confounding, which can result in an overestimation or underestimation of the effects of interest or even find an effect while in reality there is no relationship. Many factors are not taken into account such as teenage birth rates, quality of teachers and social capital (Chetty et al., 2014, 2018), which makes the results subject to omitted variable bias. Furthermore, the beta regression model was not able to capture the relationship well between intergenerational income mobility and neighborhood characteristic for high values of intergenerational income mobility.

Reason three is that the children are born between 1978 and 1983, while the neighborhood statistics date back from the year 2000 and the average rank of intergenerational income mobility is measured in 2014 and 2015. The oldest person would be 22 and the youngest would be 17 years old when the neighborhood characteristics are measured. The children grow up between 1980 and 2000. Therefore, the assumption is needed that the neighborhood statistics have not significantly changed between 1980 and 2000. Regardless, this influenced the precision of our results. Furthermore, the effects are measured on county level. The assumption is that people stayed in the same county after growing up. People could have moved to a different county after growing up, which makes the comparison between the effects on counties difficult. This effect could be more problematic for small counties than for bigger counties. The counties in this data set all have more than 10000 residents and the average population of a county in this data set is 123651. Therefore, the effect of people moving to a different county is expected to be limited. However, there is still uncertainty to what extent people have moved to a different county and what role it played in this analysis.

6.3   Suggestions for future research

Further research is needed to establish the relationship between neighborhood characteristics and intergenerational income mobility on county level. First, an experimental setup could be used to obtain experimental data or a different method could be used that can exploit the data to find causal effects such as an instrumental variable regression. However, if such an experimental setup is used, the ethical aspects of this experiment should be considered. Inspired by the Moving To Opportunity from Chetty et al. (2016), in where individuals move to a lower poverty county, a suggestion could be to randomly invest in underprivileged counties. Second, more accurate data could be used. This paper used neighborhood characteristics from 2000, while the children grew up between 1980 and 2000. A better approach would be to take the average neighborhoods statistics between 1980 and 2000 to increase reliability and representativeness of the neighborhood statistics. Third, to measure income inequality this paper took the difference between the mean and the median household income divided by the median household income. An alternative measurement for this could be proposed. A very popular measure for income inequality, which was not available on county level, is the Gini Index (Farris, 2010). This is also used in Bloome (2015). Fourth, future research could take into consideration people born at all the percentiles of the income distribution rather than only the 25th. Fifth, the beta regression with a log link function showed high errors for high values of intergenerational income mobility. Future research could employ different methods to further increase the fit of the model. Finally, future research could take into consideration the effect of people moving to a different county. A suggestion could be to compare the results of two analysis: one with counties with high relocation rates and one without counties with a high relocation rate.

7   Conclusion

This paper examined the effects of neighborhood characteristics on intergenerational income mobility on county level by using observational data from children born at the 25th percentile of the income distribution. Based on the existing literature and theory five hypotheses were formed to help answer the central question:

How can neighborhood statistics obtained from observational data help explain

intergenerational income mobility on county level?

A beta regression with a log link function was employed to test the five hypotheses. After testing the hypotheses, different conclusion were drawn. First, the effects of neighborhood characteristics on county level on intergenerational income mobility have been found in real life, in a non-experimental setting, where other externalities exist. This provides a practical foundation for further research. Second, education, poverty and family structure were found to be significantly associated with intergenerational income mobility. Higher rates of college degrees in counties are positively associated with intergenerational income mobility and higher rates of people living in poverty and higher rates of single-parent households in countes are negatively associated with intergenerational income mobility. This paper shows signs that neighborhood characteristics persits through time and may affect the next generation on county level. Therefore, economic policies that aim to create more equal opportunities for everyone should not only look at support at the individual level, but also at aggregated levels such as counties. The government should invest extra in counties with low rates of college degrees, high poverty rates, high violent crime rates and high rates of single-parent households to negate the negative effects these neighborhood characteristics have on children's financial opportunity. Finally, the conclusion is that the characteristics of a county may rub off on the next generation impacting the intergenerational financial opportunities for those who grew up in that county.

Appendix A   Variables from the Opportunity Atlas

The following contains a short description of the variables from the OA that were selected for this study.

1. *household_mean* Mean household income in the United States for the year 2000 for each county. Obtained from the 2000 Decennial Census

2. *household_median* Median household income in dollars for each county. The data for 2000 is measured in the 2000 Census.

3. *income_inequality* Difference between mean and median household income divided by the median household income.

4. *poor_share* Share of individuals in the tract for the year 2000 below the federal poverty line, measured in the decennial Census of the relevant year for the 2000 estimate for each county.

5. *crime_rate* The rate of crimes per 1000 inhabitants per county for the year 2000. Crimes include murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault.

6. *fraction_colllege* Number of people aged 25 or older for the year 2000 who have a bachelor's degree, master's degree, professional school degree, or doctorate degree, divided by the total number of people aged 25 or older in a county. Obtained from the 2000 Decennial Census.

7. *single_parent* The number of households with females heads (and no husband present) or male heads (and no wife present) with own children under 18 years old present divided by the total number of households with own children present for the year 2000 for each county.

8. *share_black* Share of Black people in the decennial Census for the year 2000 for each county.

9. *share_white* Share of White people in the decennial Census for the year 2000 for each county.

10. *share_hispanic* Share of Hispanic people in the decennial Census for the year 2000 for each county.

11. *share_asian* Share of Asian people in the decennial Census for the year 2000 for each county.

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