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The power of the future: Intergenerational income mobility and child maltreatment in the United States

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A R T I C L E I N F O

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A B S T R A C T

Background: Recent research has shown that the likelihood of children experiencing intergenerational, upward income mobility depends on the community in which they are raised. Whether parents consider their children's economic chances in their parenting decisions, however, is not well understood.
Objective: To examine the relationship between county-level income mobility–distinct from income inequality and poverty–and child maltreatment.
Participants and setting: Administrative data from the National Child Abuse and Neglect Data System: Child File for 2406 counties were merged with measures of intergenerational income mobility from Chetty et al. (2014a), including the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile by age thirty.
Methods: Weighted least squares analyses were used to empirically estimate the relationship between intergenerational income mobility and child maltreatment report rates. Maltreatment reports were also divided into subgroups by age and metropolitan status.
Results: Counties where children have a greater chance of moving up the income ladder have lower child maltreatment report rates, independent from income inequality and poverty rates. This relationship is consistent across all child ages (0–17). The relationship between upward income mobility and substantiated child maltreatment is also negatively correlated among non-metropolitan counties.
Conclusions: Children experience a lower risk for maltreatment if they are more likely to move up the income ladder in adulthood. Macroeconomic factors and policies that reduce income inequality and enhance economic mobility are likely to prevent child maltreatment.

1. Introduction

Child maltreatment remains a pervasive problem in the United States. Approximately 37% of children are the subject of a child maltreatment investigation (Kim et al., 2017), 12% are confirmed as maltreated, and 5% are removed from their homes (Yi et al., 2020). Socioeconomic status strongly and consistently predicts child maltreatment (Belsky, 1993). Children living in low socioeconomic status families are five times more likely to be the victim of child maltreatment than children from higher socioeconomic

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families (Sedlak et al., 2010). Recent research shows increasing family income can reduce child abuse and neglect (Berger et al., 2017; Cancian et al., 2013; Raissian & Bullinger, 2017), and communities with more income inequality – the distance between those at the top of the income distribution and those in the bottom – have worse child health and well-being outcomes (Eckenrode et al., 2014; Olson et al., 2010).

Research indicates that growing income inequality is linked to reduced economic mobility, as the rungs of the economic ladder grow farther apart, particularly for low-income children (Chetty et al., 2017). The American Dream promises economic mobility, but rising from the bottom to the top of the income distribution is less likely in the U.S. than many other developed countries (Ermisch et al., 2011). Unequal opportunities such as how much income a child's parents have at their birth and the opportunity surrounding a child may be more important determinants of health and human capital outcomes than in earlier generations (Chetty et al., 2017).

Chetty and colleagues convincingly show that opportunity is shaped by the ecological context in which children are raised. However, it remains unclear why some counties expand opportunity while others reduce it (Donnelly et al., 2017). Perhaps being raised in areas of high and low mobility affects the parenting. For example, areas with higher mobility may offer children different developmental contexts (e.g., better schools, less crime, lower inequality). Alternatively, resource poor areas may alter the incentives for parents to invest in their children (Doepke et al., 2019). Low mobility areas may correlate to increased child maltreatment if the ecological context acts as a stressor with few opportunities or if parents' perceived incentive to invest in their children is lower. Finally, low economic mobility may also lead parents to prioritize the present over the future, hindering their ability to invest in their children's futures (Banerjee & Duflo, 2011; Cunha, Culhane, & Elo, 2013; Shah et al., 2012).

Importantly, the influence of economic mobility is linked to, but distinct from, neighborhood influences. Neighborhood poverty, in its static form, is linked to child maltreatment (Drake & Pandey, 1996), but economic mobility relates to a dynamic process: how parental income affects child income in adulthood. No existing research has directly assessed the link between intergenerational income mobility and child maltreatment. Recent research offers the opportunity for researchers to study intergenerational income mobility and its relationship on child well-being. To the extent that greater upward mobility affects risk factors for child maltreatment, the prospect of being better off financially than one's parents may serve as a protective factor for children.

To investigate if economic advancement opportunities affect child well-being, we use a restricted version of the National Child Abuse Neglect Data Systems: Child File. These data include counties with fewer than 1000 child maltreatment reports and were made available to the research team in a data pilot program. We then created a novel dataset by merging this previously inaccessible data with intergenerational income mobility data. We find that counties where children have a greater chance of moving up the income ladder have lower rates of child maltreatment. This relationship is driven by reduced reports of neglect and physical abuse. These results imply that children experience a lower risk for maltreatment if they are more likely to move up the income ladder in adulthood.

2. Background

2.1. Inequality and parental investments in children

Parental investments (and the inability to invest) in a child are influenced by income, inequality, and mobility (Kornrich, 2016). A higher family income enables greater access to material goods (Yeung et al., 2002), provides greater ability to develop children's skills and enrich their daily learning and experiences (Corak, 2013; Kalil et al., 2016), and can be used to elicit desired behavior from children (Weinberg, 2001). High income parents are also better able to invest in nonmonetary ways, through the development of behavior and motivation, and by improving families' ability to handle stress, emotional well-being, and family relationships (Corak, 2013; Kornrich & Furstenberg, 2013; Yeung et al., 2002).

Income inequality is thought to affect child outcomes through high-income parents investing more resources in their children than low income parents. These disproportionate investments by parental income increase the disparity in health and socioeconomic outcomes of children from families across the income range (Guryan et al., 2008; Ramey & Ramey, 2010). The growing gap in incomes between advantaged and disadvantaged families differentially affects opportunities and incentives for families to invest in their children making it harder to move up the income ladder (Corak, 2013).

The role of growing income *inequality* in differential investments in children is one part of the story of how opportunity shapes mobility for children. A second strand of research describes how geographic location shapes opportunity. In this work, children's economic *mobility* is shaped by the context in which they are raised. *Inequality* and *mobility* are inherently linked – as Chetty, Hendren, Kline, and Saez (2014) describe – growing inequality means that the space between the rungs of the income ladder have grown larger, potentially making upward mobility – how easy it is to climb between rungs – more difficult. The existing research on economic mobility has largely focused on the ways in which parental income determines children's educational attainment and income. The present study builds on this evidence to descriptively examine the relationship between economic mobility and child maltreatment.

2.2. Intergenerational income mobility and child outcomes

Recent empirical evidence shows that a child's parents' income at the time of the child's birth – sometimes referred to as the "birth lottery" – is more important in contemporary society than for previous generations, in part because of the growing distance between the rich and the poor. By linking tax records of millions of parents to their children as adults, Chetty and colleagues (Chetty, Hendren, Kline, & Saez, 2014; Chetty, Hendren, Kline, Saez, & Turner, 2014; Chetty et al., 2017; Chetty & Hendren, 2018a,b) show in a series of papers that the economic prospects of children depend on where and when they grow up, even after adjusting for parental characteristics.

In one of the series' earlier papers, Chetty et al. (2017) reveal that a child's chance of earning more income than his or her parents has declined over time. In particular, children born in 1940 had a 90% chance of earning more than their parents, compared to 50% of children born in the 1980s (Chetty et al., 2017). There is also substantial variation in income mobility across the United States (Chetty, Hendren, Kline, & Saez, 2014). For example, the probability that a child starting in the bottom fifth of the national income distribution will reach the top fifth in adulthood is 4.4% in Charlotte, North Carolina compared to 10.8% in Salt Lake City, Utah and 12.9% in San Jose, California. Chetty and Hendren (2018a,b) further identify the causal effect (rather than correlations) of childhood neighborhood of origin on adult income by studying children who move. They find that growing up in a county with a one standard deviation higher intergenerational mobility increases adult income of children from low-income families by around 10% (Chetty & Hendren, 2018a). Even within labor markets there are better neighborhoods for children to grow up in terms of future earnings, without changing the cost of living (Chetty & Hendren, 2018b).

In determining mechanisms for how parental income can affect later life earnings, Chetty, Hendren, Kline, and Saez (2014) identify college attendance and adolescent childbearing as mediating factors. They find that moving from the lowest income percentile to the highest income percentile increases college attendance and reduces teenage childbearing by 68 and 30 percentage points, respectively. In other words, these authors find that much of the divergence between children from low compared to high income families emerges during adolescence, before even entering the labor market. Others have found the divergence occurs much earlier; a majority of the achievement gap exists even before children enter formal schooling in early childhood (Bradbury et al., 2015).

If initial income inequities begin their effects on subsequent mobility in early childhood, then there may also be important implications for child development and well-being. Indeed, in a recent study Donnelly et al. (2017) found that, among children from low-income families, growing up in an area with high upward mobility was associated with cognitive gains and developmental outcomes. Specifically, they found that a one standard deviation unit increase in intergenerational mobility accounts for about 20% of the difference in developmental outcomes such as externalizing behaviors and cognitive test scores between children from low- and high-income families. This relationship is independent from parental characteristics, such as intelligence and mental health. Notably, the authors find that the relationship between mobility and child development is weaker among children from high-income families.

Donnelly et al.'s (2017) finding that income mobility may influence children's cognitive and social emotional development suggests that there may be a developmental pathway by which neighborhood mobility influences parenting quality and child wellbeing. In this sense, parenting practices may be influenced by the structural neighborhood factors of high mobility areas, and parents may shift choices in the face of income immobility. This growing literature on income inequality and mobility highlights a ripe area for child well-being researchers.

2.3. *Poverty, neighborhoods, inequality, and mobility and their connection to child maltreatment*

In addition to the immediate danger child maltreatment poses to children, research also indicates a range of additional negative consequences of child maltreatment. In the short-term, child maltreatment has determinantal effects on child development. These effects span a multitude of dimensions including impeding cognitive development, creating attachment problems, increasing internalizing symptoms and behaviors, impairing social functioning, and lowering academic achievement (Lansford et al., 2002; Moylan et al., 2010). The effects are long-lasting – persisting into adolescence and adulthood – and generate substantial costs to society. Adults who were victims of child maltreatment are more likely to be unemployed, in poverty, and commit crimes (Currie & Spatz Widom, 2010; Currie & Tekin, 2012; Zielinski, 2009), ultimately costing the U.S. $428 billion each year (Peterson et al., 2018). Most tragically, child maltreatment leads to nearly 1720 child deaths each year (DHHS, 2019).

A robust literature has examined the link between individual or family-level poverty and child maltreatment. This work generally finds that poverty is an important risk factor for child maltreatment (Slack et al., 2004), and may operate through decreased resources, increased stress, and a range of mental health stressors that make providing safe and consistent care more difficult (Feely et al., 2020).

A parallel literature has focused on the role of neighborhood factors, and neighborhood poverty in particular. This work largely finds that high neighborhood poverty, low social cohesion, and low collective efficacy, among other structural factors are associated with higher rates of child maltreatment (Drake & Pandey, 1996). There are two primary pathways through which a neighborhood is hypothesized to influence child maltreatment. First, neighborhood factors may have a direct influence on parenting behaviors, as factors like weak social ties and higher levels of crime influence parenting practices. The second pathway proposes that families living in disadvantaged neighborhoods may be subject to greater surveillance and reporting of child maltreatment, and these neighborhoods have higher child maltreatment report rates as a result (Coulton et al., 2007). Alternatively, selection bias may drive the relationship between neighborhoods and child maltreatment, such that the decision to reside in a particular neighborhood is correlated with the perpetration of maltreatment.

Income inequality is also linked to child well-being in a variety of ways. On one level, income inequality shapes some forms of parenting behavior such that higher income inequality increases the stakes for success, driving high-income parents to increase their involvement and investments in their children (Doepke et al., 2019; Schneider et al., 2018). For example, research indicates that parents in low income inequality areas place a greater value on independence and imagination. Alternatively, parents in high income inequality areas value hard work much more (Doepke et al., 2019). These differing values based on economic factors are likely because returns to educational and human capital investments are greater in high income inequality places than they are in places with low income inequality. To the extent that child maltreatment is a disinvestment, this theory can be applied to this context. Indeed, previous research has shown that counties with higher income inequality have higher rates of child maltreatment (Eckenrode et al., 2014).

Emerging research suggests similar pathways for intergenerational mobility (Donnelly et al., 2017). Nevertheless, as previously described, poverty, income inequality, and income mobility are distinct constructs. For example, neighborhood and household poverty are static measures of characteristics that do not account for dynamic changes in economic well-being across generations. Income inequality is the distance between the rich and the poor, and has been increasing over the past several decades in the U.S. (Piketty & Saez, 2014). Intergenerational income mobility, in contrast, measures a process of how easy it is to move from the bottom to the top of the income ladder. Unlike inequality, which has increased since the 1970s, economic mobility within the United States has remained relatively flat during this time (Bloome, 2015; Chetty et al., 2017). Therefore it is unclear if research relating income inequality and child maltreatment can generalize to income mobility and child maltreatment. Paired with the economics literature on how income inequality manifests into income mobility, this study focuses on the role of intergenerational income mobility – distinct from household income, neighborhood poverty, and income inequality – in child maltreatment risk and prevention.

2.4. *The roles of metropolitan status, race, and ethnicity*

There is not extensive empirical evidence regarding differential child welfare system involvement among metropolitan and non-metropolitan children. The geography of poverty is changing, however, as the more affluent congregate in cities while rural and many suburban areas become increasingly poor and disadvantaged, which may be compounded by populations at risk for poverty like recent immigrants and (Allard, 2017). Recent work by Chetty et al. (2020), Weber et al. (2017) and Weber et al. (2018) indicates higher rates of upward mobility in rural counties compared to urban counties. Notably, the last 50 years have witnessed increasing county level income inequality in rural areas compared to urban areas (Butler et al., 2020). Upward mobility has been shown to be most important for child outcomes among children from the lowest income households (Donnelly et al., 2017). As a result, it may be that children in upwardly mobile non-metropolitan areas experience the greatest benefits in terms of child maltreatment.

It is well-established in the child maltreatment literature that black children are disproportionately involved in the child welfare system (Ards et al., 2003). As Drake et al. (2009) have outlined, there are a number of possible explanations for this phenomenon. First, racial disproportionately in CPS involvement may simply be the result of disproportionality in experiences of poverty among black families. Second, it could stem from visibility bias or explicit racism within the system. In this context, black families may be more likely to be surveilled by mandated reporters due to more contact with government officials, including police. Alternatively, parenting behaviors perceived as acceptable among white families may be designated as maltreatment among black families (Drake & Johnson-Reid, 2007; Roberts, 2002). Third, there could be neighborhood influences. For example, research indicates that black families living in communities in which few black families live are more likely to have children placed in foster care (Drake et al., 2009; Garland et al., 1998). Finally, recent research shows that family structure shapes differential financial investments in children, broadly speaking, whereby single and cohabiting parents invest less than married parents, largely due to differences in income (Hastings & Schneider, 2021). The inequalities in these investments are smallest among Hispanic households. Additionally, when families face a large number of socioeconomic hardships, the historically documented disadvantage of growing up in a single-parent household is mitigated for black and Hispanic children (Cross, 2020).

In sum, the geography of opportunity differentially shapes the experiences of families of color, possibly by improving neighborhood context, increasing positive parenting, and decreasing practices that may be viewed as child maltreatment. Indeed, previous research has shown that upward mobility is the lowest for black people and highest for white. Hispanic children experience levels of mobility in the middle (Chetty et al., 2020).

2.5. *The present study*

We hypothesize that greater income mobility is associated with lower rates of child maltreatment. It may be that a higher likelihood of upward mobility decreases child maltreatment through parental hope, or the idea that parents believe that investments in their children will increase the likelihood of upward mobility. Alternatively, parents in high mobility areas may have the luxury of focusing on the future more than parents in low mobility areas, who may live in circumstances that lead to more proximate causes of abuse and neglect such as substance abuse, financial stress, and mental health problems etc. Another possibility may be that greater income mobility influences child maltreatment through the opportunities available to children in areas of high mobility via structural factors such as higher quality schools or less segregation.

Similarly, lower income mobility will be associated with higher rates of child maltreatment. For example, living in an area of low economic mobility may increase the likelihood that parents maltreat their children because they view parental investments in their children as unlikely to result in positive outcomes, or because their ecological context does not foster positive parenting involvement.

3. Data and methods

3.1. *Child maltreatment reports*

Child maltreatment data come from a restricted version of the National Child Abuse and Neglect Data System (NCANDS): Child File, an administrative dataset on reports of child maltreatment to child welfare agencies. Importantly, the county where each report was made is not suppressed for counties with fewer than 1000 reports, as is done in the public use NCANDS: Child File. We obtained these restricted data through a micro-data pilot program administered by the National Data Archive on Child Abuse and Neglect (NDACAN), made available by the United States Children's Bureau. States provide basic demographic information pertaining to the report's focal child, the maltreatment type being alleged (i.e., neglect, physical abuse, etc.), if the child has had a report substantiated by child protective services (CPS) before, and the disposition of the current report (i.e., substantiated, unsubstantiated, etc.). Each report may contain up to four unique allegations of maltreatment, and the disposition of each allegation is contained in the data file.

The outcomes of interest are child maltreatment report rates. We sum the total number of child maltreatment reports in 2013 to create the numerator of the rate. We use a duplicate count in order to avoid truncating child maltreatment severity within a given county. Therefore, if a child in a given county was reported more than one time in 2013, they counted more than one time in the rate's numerator. We use US child population counts to construct the child maltreatment report rate per 100,000 children for each county in our data set.

To better understand potential mechanisms, child maltreatment report rates are disaggregated into age-specific rates (ages 0–4, 5–12, and 13–17) and maltreatment type rates (duplicate counts of neglect, physical abuse, and sexual abuse), where the denominator is 100,000 children per age group. We construct substantiation rates similar to the way the *Child Maltreatment* reports measure victimization rates (per 100,000 children): the numerator is the duplicate count of substantiations and the denominator is the child population. We also construct the prior victimization rate. This is the number of children who have ever received a substantiated child maltreatment report before relative to the child population. Ideally, the denominator for this rate would be the cumulative number of children with substantiated reports within a particular county. This risk population estimate is not available. We also cannot construct it due to data limitations, since some states provide their data to NCANDS in some years but not in other years. Therefore, we exercise caution when interpreting this measure. Finally, we explore differential effects of income mobility by child race and ethnicity and in metropolitan versus non-metropolitan counties.

Notably, although theory and prior research have focused on the link between poverty and child maltreatment, our data cannot discern the income level of families in the NCANDS data. However, prior research indicates that a disproportionate number of children involved in the child welfare system are from low-income families (Sedlak et al., 2010).

3.2. Income mobility

Measures of income mobility come from Opportunity Insights, at Harvard University (previously Equality of Opportunity project out of Stanford University). Chetty, Hendren, Kline, and Saez (2014) analyzed tax records of more than 40 million families to estimate measures of intergenerational mobility for each county in the U.S. To achieve this goal, the Chetty team first measured the incomes of parents of children born between 1980 and 1982 when the children were between 15 and 20 years old (between 1996 and 2000). They then measured the (now adult) children's family incomes when they were approximately 30 years old (between 2011 and 2012) and matched the incomes of parents to children in adulthood. They computed several county-level measures of intergenerational income mobility based on the economic standing of children as adults compared to their parents (according to the county originally measured in 1996–2000) and made these estimates publicly available.

In our primary models, we measure intergenerational economic mobility as the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty, which we refer to as *upward mobility*. This measure exhibits values between 0 and 100. Each county has one value for this measure, taking into account 12 to 18 years of intergenerational income information. Greater values of this measure indicate more mobility for children. To test the robustness of our results to the measurement of income mobility, in supplementary analyses, we use two additional measures representing absolute mobility and relative mobility. Each of these measures is discussed in Section 4.

Predictors of income immobility include living in areas with high family instability, low performing schools, and income inequality. These elements are also risk factors for child maltreatment. To isolate the relationship between intergenerational income mobility and child maltreatment, our models adjust for these local measures. Specifically, we include the Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. All of these variables come from the Opportunity Insights data repository except the total population, which comes from the National Center for Health Statistics. Some variables from the Opportunity Insights repository are constructed using the tax records of the sample used to construct the mobility measures. For example, the Gini coefficient reflects family income within each county using parents in the sample. Similarly, the teen birth rate is the fraction of female children in the sample ever claiming a dependent born while she was between the ages of 13–19. Racial makeup, family structure, local labor market conditions, and poverty rates come from the 2000 Census (the approximate time of the first measure of parents' income). Finally, each control variable was natural log transformed for ease of interpretation and comparison across each measure; the outcome measures (child maltreatment report rates) remain as rates.

3.3. Sample

To correspond to the approximate time adult children's incomes were measured in constructing the mobility measures, we used the NCANDS: Child Files Federal Fiscal Year (FFY) 2013–2015 to construct the aforementioned child maltreatment rates for the year 2013. Each NCANDS: Child File data set follows the FFY - meaning it includes data from October 1 of the preceding year to September 30 of the data set year. Therefore, the NCANDS: Child File 2013 data spans from October 1, 2012 to September 30, 2013, with the remainder of 2013 reports primarily reported in NCANDS: Child File 2014. Moreover, states may update their child maltreatment report data by adding it in to future NCANDS: Child Files. At the time of our analysis, the NCANDS: Child File 2015 was available, and so this analysis includes any child maltreatment report with a 2013 report date from the NCANDS: Child Files 2013, 2014, and 2015. Importantly, although absolute income mobility decreased dramatically between 1940 and 1970, it has stagnated since then (Chetty et al., 2017). In other words, children coming of age today have the same chances of moving up the income distribution as children born in the 1970s (Chetty, Hendren, Kline, Saez, & Turner, 2014). As expected, results using child maltreatment reports from 2011 and 2012 (constructed in an analogous fashion as 2013 reports) are similar. Therefore, this study only reports results using 2013 child maltreatment reports (results using 2011 and 2012 reports are available upon request).

In 2013 there were 3144 counties in the U.S. Due to missing child maltreatment data and missing data from Opportunity Insights, we drop 738 counties. Our analytic sample has a final sample size of 2406 counties (76% of all counties). We tend to lose counties with relatively small populations, and as a result, our analytic sample consists of more than 80% of the U.S. child population.

3.4. Statistical analysis

We estimate the relationship between intergenerational income mobility and child maltreatment using weighted ordinary least squares (OLS) regression. The first analysis assesses the relationship between overall rates of child maltreatment by maltreatment type and the primary measure of economic mobility (upward mobility). Specifically, we estimate the following model:

$$Y_c = \beta_0 + \beta_1 Mobility_c + \delta' X_c + \epsilon_c$$

where Y is the child maltreatment report rate for county c in 2013. *Mobility* represents county c's measure of upward intergenerational income mobility (where parents' incomes are measured between 1996 and 2000 and children's incomes are measured at age 30 between 2011 and 2012). X is a vector of county-level covariates adjusting for observed characteristics of a county that are correlated with both income mobility and child maltreatment. We also use the child-specific demographic information in the maltreatment reports to determine if the relationship between child maltreatment and economic mobility varies by age and child race/ethnicity. Finally, we used the United States Department of Agriculture's Rural-Urban Continuum codes to divide our county sample into metropolitan and non-metropolitan counties. This approach shows how economic mobility and child maltreatment relate in different economic and social environments and contexts. All regressions are weighted by the county child population in 2013 and have robust standard errors, which is equivalent to clustering at the county level.

4. Main results

4.1. Descriptive statistics

Table 1 presents descriptive statistics, which are weighted by the county child population. The overall child maltreatment report rate was 4678 per 100,000 children in the full sample of counties. In our analytic sample, neglect is present in about 71% of all reports, and physical abuse is present in about 24% of all reports. Sexual abuse is present in approximately 8% of reports. This distribution is similar to the national distribution of maltreatment reports. On average, in the full sample of counties, the likelihood of a child born into the bottom income quintile rising to the top income quintile by age thirty is 9.3%, with a standard deviation of 4.5.

4.2. Upward mobility and child maltreatment

Regression results for the full sample of counties are in Table 2. Each cell represents its own regression of upward mobility on the child maltreatment report rate measure. Results reveal that living in a county with a greater chance of moving up the income ladder is generally associated with lower child maltreatment reports rates. Specifically, a one percentage point increase in the probability of rising from the bottom quintile to the top quintile is associated with about 105 fewer reports of maltreatment per 100,000 children. Relative to the baseline average report rate of 4678, this estimate reflects about 2.3% fewer reports.

Moving across columns in Panel A, the relationship persists across maltreatment types: a one percentage point increase in upward mobility is associated with 2.6% fewer reports of neglect and 1.8% fewer physical abuse reports. There are also 3.4% fewer reports of children who have had a prior substantiated report. There is no significant relationship between upward mobility and either reports of sexual abuse or the overall rate of substantiated cases in our sample of counties.

Panels B, C, and D show how the relationship varies across child age group. Results are substantively similar across age groups though the relationship between upward income mobility and child maltreatment reports become muted as children age. This is true with one notable exception: upward income mobility exhibits a much stronger relationship with reports of prior abuse among adolescents compared to young and school-aged children. For example, a one percentage point increase in upward mobility is associated with between 38 and 45 fewer reports of children who have had a prior substantiated report per 100,000 children across all age groups. Relative to the mean, however, these estimates reflect approximately 3.2% and 3.6% fewer reports among young children and school-aged children, respectively, and 9.5% among adolescents.

While our models include the full set of covariate described earlier, we do not show them in order to highlight the role of mobility on child maltreatment and space limitation. However, in Appendix A we show our main results and include the coefficients of the logged Gini coefficient and logged poverty rate measures. As these variables were logged transformed, the interpretation of these variables is that a 1% change in X is associated with a B*0.01 change in the outcome variable. The Gini coefficient[1] has a negative, small in magnitude, and often statistically significant relationship with child maltreatment. In contrast the poverty rate shares a

[1] The Gini coefficient measures inequality. A measure of 0 implies perfect economic equality and a measure of 1 implies perfect economic inequality.

Table 1
Descriptive statistics.

	All counties	
	Mean	SD
Maltreatment outcomes		
All children (ages 0–17)		
Total	4677.8	2769.2
Neglect	3324.9	2458.9
Physical abuse	1132.2	745.3
Sexual abuse	374.3	279.5
Substantiations	952.1	688.9
Prior report	1212.4	1298.9
Young children (ages 0–4)		
Total	5893.4	3801.3
Neglect	4580.3	3443.0
Physical abuse	1180.7	1009.1
Sexual abuse	295.8	251.0
Substantiations	1427.3	1080.1
Prior report	1053.2	1303.2
School-aged children (ages 5–12)		
Total	4803.6	2865.2
Neglect	3320.5	2511.3
Physical abuse	1223.4	774.8
Sexual abuse	407.7	318.4
Substantiations	890.2	672.7
Prior report	1403.7	1514.2
Adolescents (ages 13–17)		
Total	3362.9	1922.6
Neglect	2169.4	1689.8
Physical abuse	950.8	583.0
Sexual abuse	339.2	869.2
Substantiations	333.9	483.8
Prior report	399.3	314.2
Mobility & covariate measures		
Upward mobility (%)	9.3	4.5
Gini coefficient (ln)	−0.82	0.23
Poverty rate (ln)	−2.20	0.47
Fraction population black (ln)	−2.88	1.46
Fraction of children with single mothers (ln)	−1.57	0.30
Parent family income in county - 99th percentile (ln)	10.99	0.31
Unemployment rate (ln)	−3.07	0.28
Fraction teen birth rate (ln)	−2.00	0.40
Population total (ln)	12.90	1.60
Sample size (number of counties)	2406	

Source: Child maltreatment data are from NCANDS: Child File 2013–2015 and mobility measures are from Chetty, Hendren, Kline, and Saez (2014). Note: Child maltreatment report rate outcomes are rates per 100,000 children, measured at the county-level. Mean values are weighted by child population. For age-specific outcomes, mean values are weighted by child population in each age group.

positive and statistically significant relationship with child maltreatment; however, the poverty rate estimates are still small in magnitude – especially when compared to the mobility measures.

4.3. Upward mobility and child maltreatment, by metropolitan status

We next evaluate whether the relationship between income mobility and child maltreatment varies by a county's metropolitan status since metropolitan areas have differential access to labor markets and employment opportunities, social services, and additional resources. Tables 3 and 4 present results for metropolitan counties and non-metropolitan counties separately. In general, the relationship between upward income mobility and maltreatment reports tends to be substantively similar in both non-metropolitan counties (Table 3) and metropolitan counties (Table 4).

Additionally, this analysis demonstrates that although there is no significant relationship between income mobility and rates of substantiations in the full sample of counties, pooling the full sample of counties together masks differences in the relationship across counties. In particular, there is a significant relationship in non-metropolitan counties (Table 3). Specifically, an increase of one percentage point in the likelihood of moving from the bottom of the income ladder to the top (*upward mobility*) is associated with 18.8 fewer substantiated reports per 100,000 children, or about 1.5% fewer substantiations in non-metropolitan counties. In contrast, mobility is not significantly associated with substantiated reports of maltreatment in metropolitan counties (Table 4).

Table 2
Regression results for full sample.

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Upward mobility	−105.50***	−87.83***	−20.40***	−3.30	−1.25	−41.16***
	(19.27)	(19.20)	(7.602)	(2.288)	(5.593)	(8.163)
Mean Y	4677.8	3324.9	1132.2	374.3	952.1	1212.4
Relative size of estimate	−2.3%	−2.6%	−1.8%	−0.8%	−0.1%	−3.4%
R^2	0.267	0.201	0.183	0.174	0.195	0.227
Panel B: young children (0–4)						
Upward mobility	−161.10***	−134.30***	−39.12***	−1.97	−11.50	−37.58***
	(25.40)	(24.96)	(9.980)	(2.006)	(8.469)	(7.298)
Mean Y	5893.4	4580.3	1180.7	295.8	1427.3	1053.2
Relative size of estimate	−2.7%	−2.9%	−3.3%	−0.3%	−0.8%	−3.6%
R^2	0.295	0.226	0.193	0.173	0.184	0.207
Panel C: school-aged children (5–12)						
Upward mobility	−102.50***	−88.60***	−16.28**	−1.65	0.82	−44.67***
	(19.88)	(19.61)	(7.747)	(2.641)	(5.441)	(9.469)
Mean Y	4803.6	3320.5	1223.4	407.7	890.2	1403.7
Relative size of estimate	−2.1%	−2.7%	−1.3%	−0.2%	0.0%	−3.2%
R^2	0.253	0.194	0.170	0.175	0.184	0.228
Panel D: adolescents (13–17)						
Upward mobility	−67.21***	−52.19***	−9.78+	−6.92***	2.20	−38.04***
	(15.63)	(15.85)	(5.903)	(2.639)	(4.603)	(8.212)
Mean Y	3362.9	2169.4	950.8	339.2	333.9	399.3
Relative size of estimate	−2.0%	−2.4%	−0.9%	−2.0%	0.6%	−9.5%
R^2	0.213	0.170	0.161	0.123	0.199	0.216

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 2406 for all regressions. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

4.4. *Upward mobility and child maltreatment, by child race/ethnicity*

Within neighborhoods, there are racial disparities in rates of upward mobility (Chetty et al., 2020). We further examine whether the relationship between income mobility and child maltreatment risk varies by child race and ethnicity. These results are in Appendix B. Income mobility predicts reduced child maltreatment similarly among non-Hispanic white and non-Hispanic black children, but among Hispanic children the opposite relationship seems to emerge (increased mobility is associated with increased maltreatment). This is a puzzling finding and may have to do with the lower level of variation in childhood investments among Hispanic families compared to non-Hispanic white and non-Hispanic black families (Hastings & Schneider, 2021).

We assert that this finding deserves increased attention in future research. Sensitivity checks discussed in Section 5 shed light on this finding.

5. Sensitivity checks

5.1. *Absolute mobility and child maltreatment*

Our primary measure of mobility thus far has been the probability that a person moves from the bottom of the income distribution in childhood to the top of income distribution in adulthood (*upward mobility*). We next examine the sensitivity of the main results to other measures of intergenerational income mobility. First, we use a measure of *absolute mobility*: the expected income percentile of children whose parents were at the 25th percentile of the distribution. For example, an absolute mobility value of 50 represents upward mobility from the 25th percentile of the income distribution to the 50th percentile. An absolute mobility value of 20 represents downward mobility from the 25th percentile to the 20th percentile. In other words, this measure takes on a value of between 0 and 100, where a greater value implies more mobility. The mean absolute value for our sample of counties is 42.0 with a standard deviation of 4.0. This value implies that, on average, the income rank of children born between 1980 and 1982 at the 25th percentile of family income is expected to be in the 42nd percentile.

Results using a measure of absolute mobility are similar to our main results (Appendix C). They indicate that an increase of one expected percentile in the income distribution for a child raised at the 25th percentile is associated with about 213 fewer reports per

Table 3
Regression results for non-metropolitan counties.

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Upward mobility	−124.6***	−97.05***	−4.512	−4.324	−18.76***	−42.44***
	(22.74)	(21.25)	(5.934)	(2.680)	(6.650)	(9.572)
Mean Y	6247.2	4489.0	1329.9	526.8	1254.4	1620.0
Relative size of estimate	−2.0%	−2.2%	−0.3%	−0.8%	−1.5%	−2.6%
R^2	0.078	0.067	0.057	0.054	0.033	0.094
Panel B: young children (0–4)						
Upward mobility	−171.1***	−137.6***	−9.712	−3.339	−27.21***	−37.51***
	(31.68)	(30.09)	(8.280)	(2.352)	(10.21)	(9.039)
Mean Y	8355.9	6505.3	1567.9	436.3	1905.6	1387.3
Relative size of estimate	−2.0%	−2.1%	−0.6%	−0.7%	−1.4%	−2.7%
R^2	0.080	0.064	0.067	0.041	0.037	0.103
Panel C: school-aged children (5–12)						
Upward mobility	−127.9***	−99.35***	−4.825	−2.441	−19.60***	−48.31***
	(23.85)	(22.00)	(6.209)	(3.009)	(6.741)	(11.46)
Mean Y	6447.3	4547.3	1406.0	571.6	1198.1	1931.1
Relative size of estimate	−2.0%	−2.2%	−0.3%	−0.3%	−1.6%	−2.5%
R^2	0.075	0.064	0.050	0.218	0.028	0.092
Panel D: adolescents (13–17)						
Upward mobility	−89.1***	−68.15***	−1.264	−7.618**	−12.87***	−37.46***
	(15.87)	(14.16)	(4.777)	(3.512)	(4.703)	(8.470)
Mean Y	4056.3	2596.9	1005.8	540.9	754.3	1360.9
Relative size of estimate	−2.2%	−2.6%	−0.1%	−1.4%	−1.7%	−2.8%
R^2	0.072	0.075	0.042	0.035	0.021	0.074

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 1424 for all regressions. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.
$^{+}p < 0.10$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

100,000 children. Relative to the mean of 4679 reports, this estimate represents about 4.5% fewer reports of child maltreatment. For all children, one additional percentile in absolute mobility is associated with about 5.6% fewer reports of neglect (184.9/3324.9), 1.8% fewer reports of physical abuse (20.74/1132.2), 1.4% more reports of sexual abuse (5.354/374.3), and 4.1% fewer reports of children who have had a substantiated report in the past (49.52/1212.4). These relationships are largely consistent across age groups. There is no significant relationship between absolute mobility and substantiated reports.

5.2. Relative mobility and child maltreatment

We next measure intergenerational income mobility as *relative mobility*: the correlation between the income ranks of parents and children in the national income distribution. Specifically, these correlations are the county-specific slopes from an OLS regression of child income percentile rank on parent income percentile rank. This measure also holds values between 0 and 100. In contrast to the previous two mobility measures, a larger correlation between child and parent income ranks represents lower mobility. The mean value for relative mobility in our sample is 32, with a standard deviation of 6.8. These results are in Appendix D. Results with this measure are substantively similar to our main results. In addition, they exhibit an age gradient, such that less income mobility is a stronger predictor of maltreatment risk for young and school-aged children than for adolescents. Interestingly, the relationship between mobility and neglect reports largely disappears when using relative mobility, except for neglect reports among young children.

5.3. The state-level effect on standard errors and estimation

The main analyses of this paper use a restricted version of the National Child Abuse and Neglect Data System (NCANDS): Child File, which were made available via a pilot program. The pilot program was abruptly pulled before we could complete all analyses. In particular, there was no opportunity to conduct analyses where the standard errors were nested at the state level, that included a state level indicator variable, a sensitivity analysis using a Poisson model (to account for the potential count nature of the data), and additional sensitivity analyses for the race/ethnicity differences. In the main analysis, we present results from the restricted version of the micro-data due to its greater geographical representation (e.g., 2406 counties rather than 807) and the ability to compare relationships across metropolitan status.

Table 4
Regression results for metropolitan counties.

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Upward mobility	−113.6***	−93.38***	−31.12***	−3.412	0.119	−47.35***
	(27.34)	(27.31)	(11.02)	(3.261)	(7.807)	(11.09)
Mean Y	4421.6	3134.9	1099.9	349.5	902.8	1145.9
Relative size of estimate	−2.6%	−3.0%	−2.8%	−0.9%	0.0%	−4.1%
R^2	0.290	0.219	0.231	0.216	0.246	0.258
Panel B: young children (0–4)						
Upward mobility	−172.3***	−142.3***	−54.14***	−1.363	−11.38	−42.26***
	(35.88)	(35.45)	(14.53)	(2.945)	(12.23)	(9.926)
Mean Y	5491.4	4266.1	1117.6	272.8	1349.2	998.6
Relative size of estimate	−3.1%	−3.3%	−4.8%	−0.4%	−0.8%	−4.2%
R^2	0.310	0.240	0.225	0.215	0.218	0.231
Panel C: school-aged children (5–12)						
Upward mobility	−109.6***	−94.40***	−25.73**	−1.842	2.889	−51.50***
	(28.03)	(27.71)	(11.22)	(3.793)	(7.469)	(12.85)
Mean Y	4535.3	3120.2	1193.6	381.0	839.9	1317.6
Relative size of estimate	−2.4%	−3.0%	−2.2%	−0.3%	0.2%	−3.9%
R^2	0.274	0.211	0.223	0.218	0.238	0.257
Panel D: adolescents (13–17)						
Upward mobility	−72.45***	−53.51**	−17.78**	−7.786**	3.961	−44.78***
	(22.27)	(22.29)	(8.517)	(3.538)	(5.941)	(10.98)
Mean Y	3249.8	2099.7	941.8	376.2	581.9	1029.3
Relative size of estimate	−2.2%	−2.5%	−1.9%	−2.1%	0.5%	−4.4%
R^2	0.254	0.203	0.220	0.161	0.278	0.267

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 982 for all regressions. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.
$^{+}p < 0.10$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

Although there is currently no way to access the full restricted data, these sensitivity analyses can be completed using the NCANDS: Child File data that are typically and publicly available to researchers. Table 5 shows the results of four different analyses. First, the main results of the paper are displayed for ease of comparison in Panel A. Next, results from replicating the paper's methods on the public use NCANDS: Child File data are shown (note: the number of counties in the sample is one-third of that in the restricted data). Panel C presents an analysis where the standard errors are nested at the state level. Finally, a state level indicator variable is added to the analysis, and the standard errors remain nested at the state level. Together, the results from Table 5 show that the main results are robust to sample selection (Panel B), the treatment of the standard error (Panel C), and the inclusion of a state indicator variable (Panel D). Results from the Poisson model are also comparable and available upon request.

Finally, Appendix E reports sensitivity checks in a similar fashion for the child race/ethnicity analyses. Specifically, this table shows the maltreatment report rates as the number of reports for each race/ethnicity relative to the child population in each race/ethnicity. Results are sensitive to the selection of the denominator, treatment of the standard error, and the addition of a state indicator variable. Namely, Panel E shows that the relationship between upward mobility and child maltreatment reports is larger for children of black race and Hispanic ethnicity than white children. Indeed, in the public NCANDS: Child File data typically available, there is no significant relationship between mobility and child maltreatment reports among white children.

6. Discussion

In this study, we find that greater income mobility is significantly associated with lower rates of maltreatment in counties across the U.S, even after accounting for income inequality and poverty. These results are most pronounced among rates of neglect, physical abuse, and repeat maltreatment. The relationship is generally consistent across age groups. These results are also robust to various measures of income mobility.

Our findings imply that if parents view their children as having greater chances for a better economic future they may be less likely to be reported for child abuse and neglect. Our results are consistent with a recent study that found that among children from low-income families, growing up in a county with high upward income mobility is associated with fewer externalizing behavioral problems and better cognitive test scores between ages 3 and 9 (Donnelly et al., 2017). Fewer behavioral problems may even be a mechanism through which upward income mobility is related to child maltreatment (Grogan-Kaylor et al., 2008; Mills et al., 2013).

Table 5
Sensitivity analysis to standard error and state indicator variable.

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: restricted NCANDS data, as reported in Table 2						
Upward mobility	−105.50***	−87.83***	−20.40***	−3.30	−1.25	−41.16***
	(19.27)	(19.20)	(7.60)	(2.288)	(5.593)	(8.16)
Mean Y	4678	3325	1132	374	952	1212
Relative size of estimate	−2.30%	−2.60%	−1.80%	−0.8%	−0.1%	−3.40%
R^2	0.267	0.201	0.183	0.174	0.195	0.227
Includes state indicator variable	N	N	N	N	N	N
SEs nested at state level	N	N	N	N	N	N
Sample size	2406					
Panel B: non-restricted NCANDS data, same method as reported in Table 2, robust SE						
Upward mobility	−177.14***	−137.92***	−43.60***	−5.23	−8.55	−94.33***
	(32.68)	(31.27)	(11.88)	(3.21)	(8.88)	16.60
Mean Y	4707	3406	1143	362	956	1259
Relative size of estimate	−3.76%	−4.05%	−3.81%	−1.44%	−0.89%	−7.49%
R^2	0.27	0.23	0.14	0.18	0.23	0.20
Includes state indicator variable	N	N	N	N	N	N
SEs nested at state level	N	N	N	N	N	N
Sample size	807					
Panel C: non-restricted NCANDS data, standard errors nested at state level						
Upward mobility	−177.14***	−137.92**	−43.60	−5.23	−8.55	−94.33**
	(59.73)	(59.33)	(28.36)	(5.50)	(13.89)	(36.55)
Mean Y	4707	3406	1143	362	956	1259
Relative size of estimate	−3.76%	−4.05%	−3.81%	−1.44%	−0.89%	−7.49%
R^2	0.27	0.23	0.14	0.18	0.23	0.20
Includes state indicator variable	N	N	N	N	N	N
SEs nested at state level	Y	Y	Y	Y	Y	Y
Sample size	807					
Panel D: non-restricted NCANDS data, standard errors nested at state level, includes state indicator variable						
Upward mobility	−130.42**	−119.39**	−22.27*	−5.67	−24.25**	−40.10
	(61.63)	(54.90)	(11.45)	(4.46)	(10.80)	(32.51)
Mean Y	4707	3406	1143	362	956	1259
Relative size of estimate	−2.77%	−3.51%	−1.95%	−1.57%	−2.54%	−3.19%
R^2	0.61	0.68	0.68	0.64	0.58	0.72
Includes state indicator variable	Y	Y	Y	Y	Y	Y
SEs nested at state level	Y	Y	Y	Y	Y	Y
Sample size	807					

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Pairing our study with Donnelly et al. (2017) cumulatively implies that the health and developmental trajectories of economically disadvantaged children depends on the residential contexts in which they are raised. Although our study is not exclusive to children from low-income households, children from low-income households are substantially overrepresented in the child welfare system. This finding is especially salient for young children, where one might expect parental time investments to be particularly important and intensive.

Our study also contributes significant and important findings to the literature on the relationship between socioeconomic factors and child maltreatment. A substantial body of research explores the role of poverty in the risk for child maltreatment. Individual-level poverty is associated with increased risk for child abuse and neglect (Berger, 2004; Sedlak et al., 2010; Slack et al., 2004). Similarly, neighborhood poverty is closely linked with child maltreatment risk (Coulton et al., 1995; Drake & Pandey, 1996). A growing line of research has sought to determine a more causal link between economic hardship and child maltreatment. This literature has drawn on aggregate measures of unemployment, home foreclosures, consumer sentiment, and mass layoffs and has found mixed results (Berger et al., 2015; Lindo et al., 2018; Raissian, 2015; Schenck-Fontaine et al., 2017; Schenck-Fontaine & Gassman-Pines, 2020; Schneider et al., 2017). Beyond income levels, counties with larger income inequality also have higher child maltreatment report rates (Eckenrode et al., 2014), and job losses take different forms across areas with varying levels of income inequality (Schenck-Fontaine & Gassman-Pines, 2020). To our knowledge, this study is the first to specifically distinguish intergenerational income mobility from household income, economic hardship, neighborhood poverty, unemployment, and income inequality as a risk factor for child maltreatment. Our results are consistent with much of this earlier literature in that neglect and physical abuse are the most sensitive types of maltreatment to these macroeconomic factors.

Finally, our results also highlight a recently developing finding relating to the differential role economic factors play in child maltreatment across metropolitan and non-metropolitan areas (Raissian, 2015). This is also reflected in the broader neighborhoods literature, where emerging research indicates stark divides in inequality and mobility between urban and rural geographies (Weber et al., 2017). Our results imply that particularly in non-metropolitan areas, children are less likely to be victims of confirmed maltreatment if they are more likely to move up the income ladder in adulthood. This finding implies that if parents view their children as having greater chances for a better economic future, they may invest more time and resources into their children. This finding may also suggest it is more challenging to overcome income immobility in non-metropolitan areas where there are often fewer labor market opportunities.

Although this is the first study of the relationship between income mobility and child maltreatment, it is not without limitations. First, we use administrative data of reports to CPS agencies to measure maltreatment. There is disagreement on whether CPS reports are undercounts (Finkelhor, 2005) or overcounts (Besharov, 1994) of the true incidence of child maltreatment. They trend proportionally with other measures of maltreatment (Drake et al., 2011), however, and are generally considered reliable data. We note that our results find an inconsistent association between mobility and child maltreatment report rates and mobility and child maltreatment substantiation rates. We prefer report rates as the primary measure of child well-being because they are less influenced by CPS policies, and capture the extent to which a community member or professional is concerned about the well-being of a child. Without a doubt, these data measure the rate at which children and their families come before and are at risk of CPS involvement. All else equal, we believe that a reduction in the report rate signals an improvement in child well-being in a specific community. This also signals a need for increased research surrounding the distinctions between report rates and substantiation rates, more generally.

Similarly, although the mobility measures we use are the most well-respected measures of mobility in the research community, they, by definition, must cover many years. Individual-level child maltreatment report data to match the sample used in constructing the mobility measures do not exist, so choices must be made in constructing both the outcome and other covariates in the model. We used child maltreatment report data from 2013 and covariates from Opportunity Insights (either within-sample or from the 2000 Census) as approximations, though the outcome year of choice is not consequential for the main results. Finally, the mobility measures do not consider geographic mobility during the interim.

We are also unable to identify the precise mechanisms through which income mobility and child maltreatment are related. By studying across maltreatment types and child ages, however, we provide a glimpse into how income mobility may affect maltreatment risk, and future research should explore the various pathways and different combinations of levels of mobility and inequality by geography.

Finally, our results are limited in their causal interpretation. Theoretically, the correlational relationship between income mobility and child maltreatment could be reversed, such that child maltreatment reports lead to income mobility. However, the mobility measures have been constructed using data from earlier time periods than the child maltreatment measures reflect. Further, CPS case workers may be able to provide resources to families facing economic hardship due to income immobility that could potentially enhance mobility. For these reasons, it is unlikely that CPS involvement leads to income immobility.

7. Conclusion

Society has historically viewed child maltreatment as a family problem, typically offering interventions at the case or family-level. Indeed, the American Academy of Pediatrics (AAP) Committee on Child Abuse and Neglect issued a report in 2010 identifying ways to prevent child maltreatment (Flaherty et al., 2010). This report focused on individual-level actions of pediatricians, hospital-based programs, and community-level prevention programs. This perspective has been successful for identifying the risk and protective factors for sexual and physical abuse and has led to many effective prevention strategies (Ryan et al., 2016).

The results of our study, however, suggest that child maltreatment prevention may require a bigger picture framework integrating macroeconomic factors. Specifically, enhancing economic opportunities for children could possibly reduce child maltreatment. These macroeconomic factors, such as economies, labor markets, economic equality, and governmental affairs, play a large role in family circumstances and decision-making. Policies and programs that focus on narrow targets such as family-level interventions are unlikely to have success on a broad scale. Policies that address the underlying social and economic problems are more likely to reduce child maltreatment (Bullinger et al., 2020; Feely et al., 2020). For example, there is overwhelming evidence that increasing the minimum wage reduces poverty, and recent research shows that increases in the minimum wage can reduce child maltreatment (Raissian & Bullinger, 2017). The Earned Income Tax Credit (EITC) has also shown significant progress in reducing inequality (Hoynes & Patel, 2015) and this policy tool has also translated into less child maltreatment (Berger et al., 2017; Kovski et al., 2021), and fewer foster care entries (Biehl & Hill, 2018). Finally, educational inequities perpetuate income inequality. Investing in early childhood education, such as through universal preschool, can reduce the early childhood income-based achievement gap (Duncan & Sojourner, 2013), and is also associated with lower rates of child maltreatment (Green et al., 2014). Future research should determine the extent to which these policies and others have spillovers onto child maltreatment to better understand their scope.

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Appendix A. Regression results for full sample. Inequality and poverty rate coefficients shown

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Upward mobility	−105.50***	−87.83***	−20.40***	−3.30	−1.25	−41.16***
	(19.27)	(19.20)	(7.602)	(2.288)	(5.593)	(8.163)
Inequality (ln)	−944.3	−773.8	−373.1**	51.94	−285.9	−580.3**
	(624.4)	(677.3)	(159.5)	(63.19)	(205.9)	(229.5)
Poverty rate (ln)	1572.1***	1651.6***	568.6***	70.45+	485.0***	596.7***
	(385.0)	(391.2)	(113.2)	(41.13)	(96.85)	(147.5)
Mean Y	4677.8	3324.9	1132.2	374.3	952.1	1212.4
Relative size of estimate	−2.3%	−2.6%	−1.8%	−0.8%	−0.1%	−3.4%
R-squared	0.267	0.201	0.183	0.174	0.195	0.227
Panel B: young children (0–4)						
Upward mobility	−161.10***	−134.30***	−39.12***	−1.97	−11.50	−37.58***
	(25.40)	(24.96)	(9.980)	(2.006)	(8.469)	(7.298)
Inequality (ln)	−954.0	−663.1	−373.4+	110.5**	−309.0	−461.2***
	(818.0)	(787.4)	(225.1)	(53.28)	(253.7)	(178.3)
Poverty rate (ln)	2137.6***	2082.0***	671.9***	39.71	815.0***	506.6***
	(508.0)	(506.4)	(152.8)	(32.78)	(148.3)	(138.6)
Mean Y	5893.4	4580.3	1180.7	295.8	1427.3	1053.2
Relative size of estimate	−2.7%	−2.9%	−3.3%	−0.3%	−0.8%	−3.6%
R-squared	0.295	0.226	0.193	0.173	0.184	0.207
Panel C: school-aged children (5–12)						
Upward mobility	−102.50***	−88.60***	−16.28**	−1.65	0.82	−44.67***
	(19.88)	(19.61)	(7.747)	(2.641)	(5.441)	(9.469)
Inequality (ln)	−942.4	−857.2	−382.0**	91.37	−300.9	−625.7**
	(637.7)	(694.3)	(165.1)	(75.37)	(204.3)	(258.1)
Poverty rate (ln)	1504.7***	1624.0***	579.9***	67.57	427.0***	695.8***
	(396.2)	(398.5)	(116.2)	(47.77)	(92.36)	(167.2)
Mean Y	4803.6	3320.5	1223.4	407.7	890.2	1403.7
Relative size of estimate	−2.1%	−2.7%	−1.3%	−0.2%	0.0%	−3.2%
R-squared	0.253	0.194	0.170	0.175	0.184	0.228
Panel D: adolescents (13–17)						
Upward mobility	−67.21***	−52.19***	−9.78+	−6.92***	2.20	−38.04***
	(15.63)	(15.85)	(5.903)	(2.639)	(4.603)	(8.212)
Inequality (ln)	−1043.9+	−848.0	−369.4***	−65.73	−295.7	−607.2**
	(573.7)	(700.8)	(120.2)	(64.76)	(216.5)	(301.1)
Poverty rate (ln)	976.3***	1135.7***	416.2***	107.2**	231.1***	509.9***
	(308.3)	(319.2)	(89.09)	(50.87)	(82.43)	(152.8)
Mean Y	3362.9	2169.4	950.8	339.2	333.9	399.3
Relative size of estimate	−2.0%	−2.4%	−0.9%	−2.0%	0.6%	−9.5%
R-squared	0.213	0.170	0.161	0.123	0.199	0.216
Sample size for all models	2406	2406	2406	2406	2406	2406

Notes: Data come from NCANDS: Child file 2013 and Chetty, Hendren, Kline, and Saez (2014) and Chetty, Hendren, Kline, Saez, and Turner (2014). Each cell represents its own regression. Sample size = 2406 for all regressions. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, total crime rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Appendix B. Regression results for full sample of counties, by child race/ethnicity

	Report rate (per 100,000 children)				
	Non-Hispanic White	Non-Hispanic Black	Hispanic	Unknown	Other
Upward mobility	−95.99***	−40.81***	42.80***	−18.33***	6.847**
	(13.37)	(8.033)	(7.789)	(4.640)	(3.218)
Mean Y	2062	1047	913	390	158
Relative size of estimate	−4.7%	−3.9%	4.7%	−4.7%	4.3%
R^2	0.373	0.523	0.460	0.057	0.042

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 2406 for all regressions. The outcome represents the number of reports among children of a particular race/ethnicity relative to the total child population. Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Appendix C. Regression results for full sample of counties, absolute mobility

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Absolute mobility	−212.6***	−184.9***	−20.74+	5.354+	6.837	−49.52***
	(27.38)	(26.29)	(10.85)	(3.078)	(7.832)	(10.70)
Mean Y	4677.8	3324.9	1132.2	374.3	952.1	1212.4
Relative size of estimate	−4.5%	−5.6%	−1.8%	1.4%	0.6%	−4.1%
R^2	0.284	0.217	0.181	0.174	0.196	0.226
Panel B: young children (0–4)						
Absolute mobility	−272.9***	−232.4***	−37.58**	6.631**	1.430	−40.91***
	(36.31)	(35.18)	(14.94)	(2.661)	(12.09)	(9.950)
Mean Y	5893.4	4580.3	1180.7	295.8	1427.3	1053.2
Relative size of estimate	−4.6%	−5.1%	−3.2%	2.2%	0.1%	−3.9%
R^2	0.306	0.235	0.188	0.175	0.183	0.204
Panel C: school-aged children (5–12)						
Absolute mobility	−216.3***	−193.1***	−15.74	8.046**	9.682	−52.79***
	(28.22)	(26.47)	(10.84)	(3.597)	(7.628)	(12.37)
Mean Y	4803.6	3320.5	1223.4	407.7	890.2	1403.7
Relative size of estimate	−4.5%	−5.8%	−1.2%	2.0%	1.0%	−3.8%
R^2	0.270	0.212	0.168	0.177	0.185	0.226
Panel D: adolescents (13–17)						
Absolute mobility	−168.0***	−145.0***	−14.59+	0.187	1.883	−52.16***
	(21.32)	(20.64)	(8.145)	(3.488)	(5.870)	(10.43)
Mean Y	3362.9	2169.4	950.8	339.2	333.9	399.3
Relative size of estimate	−5.0%	−6.7%	−1.5%	0.0%	0.3%	−13.1%
R^2	0.239	0.196	0.162	0.119	0.198	0.218

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 2406 for all regressions. Absolute mobility is the expected income percentile of children whose parents are at the 25th percentile of the distribution. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

Appendix D. Regression results for full sample of counties, relative mobility

	Report rate (per 100,000 children in each age group)					
	Total	Neglect	Physical	Sexual	Substantiated	Prior
Panel A: all children						
Relative mobility	56.83**	28.22	19.44**	9.335***	−0.199	25.49***
	(23.93)	(21.40)	(8.046)	(1.650)	(5.793)	(7.972)
Mean Y	4677.8	3324.9	1132.2	374.3	952.1	1212.4
Relative size of estimate	1.2%	0.8%	1.7%	2.5%	0.0%	2.1%
R^2	0.264	0.194	0.189	0.192	0.195	0.226
Panel B: young children (0–4)						
Relative mobility	93.82***	59.59**	31.93***	5.981***	5.515	13.81**
	(32.32)	(28.36)	(11.84)	(1.378)	(8.809)	(6.922)
Mean Y	5893.4	4580.3	1180.7	295.8	1427.3	1053.2
Relative size of estimate	1.6%	1.3%	2.7%	2.0%	0.4%	1.3%
R^2	0.292	0.220	0.199	0.183	0.184	0.199
Panel C: school-aged children (5–12)						
Relative mobility	54.94**	28.92	15.65**	9.642***	−0.731	30.00***
	(24.16)	(21.24)	(7.842)	(1.919)	(5.510)	(9.072)
Mean Y	4803.6	3320.5	1223.4	407.7	890.2	1403.7
Relative size of estimate	1.1%	0.8%	1.3%	2.4%	0.0%	2.1%
R^2	0.250	0.187	0.174	0.191	0.184	0.228
Panel D: adolescents (13–17)						
Relative mobility	27.15	−0.158	12.75**	11.73***	−3.944	27.82***
	(17.48)	(17.09)	(5.319)	(1.856)	(4.747)	(8.353)
Mean Y	3362.9	2169.4	950.8	339.2	333.9	399.3
Relative size of estimate	0.8%	0.0%	1.3%	3.5%	−0.9%	7.0%
R^2	0.208	0.163	0.168	0.143	0.200	0.219

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 2406 for all regressions. Relative mobility is the correlation between the income ranks of parents and children in the national income distribution. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Appendix E. Sensitivity analyses, by child race/ethnicity

	Report rate (per 100,000 children in each race/ethnicity group)		
	White	Black	Hispanic
Panel A: original results from Appendix B, restricted NCANDS, robust SE			
Upward mobility	−95.99***	−40.81***	42.80***
	(13.37)	(8.033)	(7.789)
Mean Y	2062	1047	913
Relative size of estimate	−4.7%	−3.9%	4.7%
R^2	0.373	0.523	0.460
Includes state indicator variable	N	N	N
Sample size	2406		
Panel B: non-restricted NCANDS, replicate denominators, robust SE			
Upward mobility	−83.93***	−56.11***	47.28***
	(17.67)	(12.57)	(13.57)
Mean Y	1713	1039	1014
Relative size of estimate	−4.90%	−5.40%	4.66%
R^2	0.34	0.52	0.49
Includes state indicator variable	N	N	N
Sample size	807		
Panel C: non-restricted NCANDS, race-county specific denominators, robust SE			
Upward mobility	−3.70	−321.99***	−70.31*
	(24.95)	(78.65)	(40.53)
Mean Y	3235	6005	3553
Relative size of estimate	−0.11%	−5.36%	−1.98%
R^2	0.29	0.13	0.11

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(*continued*)

	Report rate (per 100,000 children in each race/ethnicity group)		
	White	Black	Hispanic
Includes state indicator variable	N	N	N
Sample size	807		
Panel D: non-restricted NCANDS, race-county specific denominators, SE nested in state			
Upward mobility	−3.70	−321.99***	−70.31+
	(44.49)	(120.93)	(39.52)
Mean Y	3235	6005	3553
Relative size of estimate	−0.11%	−5.36%	−1.98%
R^2	0.29	0.13	0.11
Includes state indicator variable	N	N	N
Sample size	807		
Panel E: non-restricted NCANDS, race-county specific denominators, SE nested in state, state indicator variable			
Upward mobility	−65.23	−257.28**	−151.24***
	(51.37)	(107.69)	(35.36)
Mean Y	3235	6005	3553
Relative size of estimate	−2.02%	−4.28%	−4.26%
R^2	0.58	0.47	0.40
Includes state indicator variable	Y	Y	Y
Sample size	807		

Notes: Data come from NCANDS: Child file 2013–2015 and Chetty, Hendren, Kline, and Saez (2014). Each cell represents its own regression, where the unit of analysis is the county. Sample size = 2406 for all regressions. The outcome represents the number of reports among children of a particular race/ethnicity relative to the total child population in that race/ethnicity (Panels C–E). Upward mobility is the probability that a child born in the bottom quintile of the national income distribution reaches the top quintile of the national income distribution by age thirty. All models include the log transformation of the following: Gini coefficient, fraction of the county that is black, fraction of children with single mothers, median family income, teen birth rate, unemployment rate, poverty rate, and total population. Robust standard errors in parentheses.

+ $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

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