CHILDREN'S INDIRECT EXPOSURE TO THE U.S. JUSTICE SYSTEM: EVIDENCE FROM LONGITUDINAL LINKS BETWEEN SURVEY AND ADMINISTRATIVE DATA*

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Abstract

Children's indirect exposure to the justice system through biological parents or co-resident adults is both a marker of their own vulnerability and a measure of the justice system's expansive reach in society. Estimating the size of this population has historically been hampered by inadequate data resources, including the inability to (1) observe non-incarceration events, (2) follow children throughout their childhood, and (3) measure adult non-biological parent cohabitants. To overcome these challenges, we leverage billions of restricted administrative and survey records linked with Criminal Justice Administrative Records System data, and find substantially larger exposure rates than previously reported: prison – 9% of children born between 1999–2005, felony conviction – 18%, and any criminal charge – 39%. Charge exposure rates exceed 60% for Black, American Indian, and low-income children. While broader definitions reach a more expansive

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population, strong and consistently negative correlations with childhood well-being suggest these remain valuable predictors of vulnerability. Finally, we document substantial geographic variation in exposure, which we leverage in a movers design to estimate the effect of living in a high-exposure county during childhood. We find that children moving into high-exposure counties are more likely to experience post-move exposure events and exhibit significantly worse outcomes by age 26 on multiple dimensions (earnings, criminal activity, teen parenthood, mortality); impacts are strongest for those who moved at earlier ages. *JEL* Codes: K14, K42, J12, I32.

1 Introduction

Both human capital investments and deprivation can have critical and dynamic impacts on children throughout their lives (Currie and Almond, (2011). Investments in the domains of health (Black et al., 2007; Campbell et al., 2014), education (Deming, 2009; Dynarski et al., 2013), housing (Chetty et al., 2016), and financial well-being (Hoynes et al., 2016) made before children become adults can influence a lifetime of outcomes, including educational attainment, employment, earnings, and mortality. The implications of these findings for economic inequality, racial disparities, and intergenerational mobility motivate a wide range of U.S. public policies that aim to equalize opportunity regardless of one's family background.

One area that has received growing attention is the influence of parental involvement in the criminal justice system (e.g., National Research Council, (2014; Wildeman, 2009; Billings, 2018; Norris et al., 2021; Arteaga, 2021). A half century of criminal justice policy has expanded both the share and degree of contact that the U.S. population has with the formal justice system, reflected in both the growing number of individuals with criminal histories and dramatic expansions in imprisonment rates. Contractions in safety net assistance and social support programs may also contribute to this pattern by increasing rates of illicit activity in the population overall (Deshpande and Mueller-Smith, 2022). Whether justice involvement reflects household shocks to financial or emotional stability, or exposure of children to undesirable living circumstances, the ramifications of this caseload growth may potentially be felt for decades to come because of intergenerational spillovers within households.

Precisely measuring exposure by biological parents or co-resident adults to the justice system comes with several challenging hurdles. Data limitations and a prior focus on incarceration have yielded almost exclusively exposure estimates of parental incarceration in prison or jail.[1] However, many other forms of contact with the justice system exist, such as arrests, charges, and convictions, which may also independently impact child development, whether because of the justice system itself or the underlying criminal activity those events represent.

[1] For an example of prominent studies focusing on incarceration or jail, see Mumola (2000); Wildeman (2009); Lee et al. (2015); Wildeman and Andersen (2015); Billings (2018); Norris et al. (2021); Enns et al. (2019).

Likewise, existing estimates typically quantify contemporaneous exposure at a given point in time (e.g., Mumola, 2000; Glaze and Maruschak, 2008), which may be insufficient if these events produce long-term scarring effects.[2] Finally, the literature predominately focuses on biological parents as the originating sources of justice exposure by adults in the home, which overlooks a well-established literature on changing household structure in the U.S. (see Smock and Schwartz, 2020, for a recent review), especially among racial and ethnic minority populations (Raley et al., 2015).

In this paper, we take a new approach by leveraging billions of federal tax, household survey, and program participation records linked with Criminal Justice Administrative Records System (CJARS; Finlay and Mueller-Smith, 2020) data to quantify what share of recent birth cohorts in the United States have ever experienced exposure by biological parents or co-resident adults to multiple stages of the U.S. criminal justice system. We address three primary shortcomings in prior estimates by accounting for: (1) multiple forms of exposure beyond just incarceration, (2) cumulative exposure over childhood relative to point-in-time exposure, and (3) sources of exposure from adults who are not biological parents (e.g., other adult caregivers or household members). To accomplish this, we build national longitudinal relationship and residence crosswalks that incorporate novel linkages across a range of data sources: decennial census and American Community Survey household rosters, IRS Form 1040 tax returns, Social Security Administration SS-5 registrations, and beneficiary rosters from the Department of Housing and Urban Development, the Indian Health Service, and the Centers for Medicare and Medicaid Services.

Starting with the most common measure used in the literature, we find that 0.8% of children in 1999–2005 birth cohorts in our sample of states had a biological parent in prison in any given year of childhood. The share of children exposed to the criminal justice system in any given year increases when we expand our definition to other events, such as felony convictions (0.9%), felony charges (1.2%), and any criminal charges (3.7%). The cumulative share of children ever exposed to criminal justice events, which accounts for scarring effects of exposure, dwarfs the point-in-time estimates with 3.6%, 9.2%, 11.4%, and 26% of children exposed to incarcerations, felony convictions, felony charges, or any criminal charges of biological parents during childhood. Even further, cumulative exposure estimates are 50% to 140% larger once other potential caregivers are also considered: 8.8%, 18.3%, 21.4%, and 38.9%. Corresponding estimates for exposure of Black children through potential caregivers

[2] Studies that do seek to quantify the size of cumulative exposure, either apply strong assumptions to aggregate data using a life tables methodology from demographic research (Wildeman, 2009; Wildeman and Andersen, 2015) or use small longitudinal surveys like the newly fielded Family History of Incarceration Survey (Enns et al., 2019), which was conducted as part of the AmeriSpeak panel data collection effort (N=4,041, 34% response rate). Smaller survey collections unfortunately lack the sample size and response rates to precisely estimate the degree of child exposure in the population, much less demographic, spatial, and temporal differences within the population.

are 20%, 35%, 42%, and 62%.[3] We observe a strong household income gradient with regard to all types of exposure, although the benefit of household income at birth varies by racial and ethnic background.

One could argue that we have diluted the concept of indirect exposure, resulting in larger prevalence rates but less serious shocks for children. To study this hypothesis, we investigate how these new measures correlate with household survey data on child well-being (e.g., poverty, behind age-appropriate grade level, cognitive difficulty/stress, grandparent as primary caregiver) after controlling for place of birth, age, household income at birth, race, and sex. We find that the estimated relationships between exposure and child outcomes are often remarkably similar regardless of the type of criminal justice exposure, the recency of the event, or whether a parent or other coresident adult was the source of exposure.

As a final exercise, we map the geographic heterogeneity of child indirect exposure across U.S. counties and leverage this variation to study the effect of living in a high-exposure area using children who move during childhood to different places and at different ages. We observe substantial inter-county variation; children living in the 75th relative to the 25th percentile of criminal justice exposure are 4.0 percentage points (↑ 34%) and 2.4 percentage points (↑ 40%) more likely to indirectly experience felony convictions and incarcerations through biological parents and/or a co-resident adult. The causal effect of geography is confirmed through the movers analysis; those who move into high-exposure jurisdictions are significantly more likely to experience a post-move exposure event. We find that such dynamics have long-term implications: increasing the child's own likelihood of becoming involved in the justice system by age 26, reducing their early adult employment and earnings, increasing the risk of becoming a teen parent, and having a greater likelihood of death by age 26. This holds true even after controlling for other county characteristics, like the local economic mobility rate, education spending per student, racial and income segregation, and local industrial composition.

To our knowledge, we are the first to leverage U.S. administrative data to estimate: (1) the prevalence of children's exposure to a range of types of parental contact with the criminal justice system, (2) cumulative exposure estimates over the duration of childhood, and (3) the magnitude of exposure originating from adult household members who are not biological parents.[4] These expanded measures fundamentally redefine the scope of the spillover population in this literature, shifting the narrative from less than one-in-forty to almost one-in-two minors in the U.S. Moreover, our newly documented relationships between indirect exposure,

[3] Estimates on the intensive margin of exposure provide further evidence of racial disparities. These are discussed in Section 6.

[4] For estimates of exposure using register data in other countries, see Wildeman and Andersen (2015) using Danish registries and Hjalmarsson and Lindquist (2012, 2013) using Swedish registries.

child development, and young adult outcomes provide evidence suggesting that recent crime and social policy may have had important unintended consequences on the most vulnerable members of society, in ways that could undermine the ability of children to realize their full potential.

2 Why indirect exposure matters for children

Indirect exposure to the justice system simultaneously reflects two broad conceptual influences on child development and well-being. First, adult involvement in the justice system could be an indication that the household is actively in a moment of crisis (financial, health, physical safety, or otherwise) that puts the child at risk. This reflects more the circumstances that led to justice involvement in the first place, rather than the direct impact of the justice system itself. But a second channel also arises since exposure can represent the potential initiation of justice-based interventions to the adult that could have ramifications for the entire household. Both of these channels are discussed in detail below.

Households under strain or in crisis. Being charged, convicted, or placed in correctional supervision may indicate an unsafe or harmful environment for children in the household. Criminal charges could reflect allegations of direct harm to the child, including: domestic violence, abuse and neglect, sexual assault of a minor, or child pornography. Doyle and Aizer (2018) provide a recent review of the literature, which finds that abuse, neglect, and maltreatment is linked with future violence and criminal activity (Widom, 1989; Currie and Tekin, 2012), impeded brain development (Petersen et al., 2014), and worsened education and earnings trajectories (Currie and Widom, 2010). Together, these impacts are estimated to generate substantial social costs (Fang et al., 2012; Peterson et al., 2018).

Charges may also reflect adult conduct, apart from the child, that still may put the child at risk, including: indications of substance abuse (possession of illicit drugs, abuse of prescription medication, driving while intoxicated), acute financial hardship (burglary, fraud, prostitution, robbery, or theft), or emotional and mental instability (disorderly conduct, violent offenses, intimate partner violence). Growing up with a parent who struggles with substance abuse has been associated with child behavioral problems (Chatterji and Markowitz, 2001), incidents of neglect and foster care (Cunningham and Finlay, 2013), and poorer labor market outcomes (Balsa, 2008). Child poverty has been tied to impacts on physical and mental health, human capital formation, youth delinquency, and economic self-sufficiency (see National Academies of Sciences, Engineering, and Medicine, (2019, for a recent review of the literature). Intimate partner violence and household conflict have been shown to worsen birth outcomes (Aizer, 2010; Currie et al., 2022), increase disruptive behavior (Carrell and Hoekstra, 2010; Herrenkohl et al., 2008; Levendosky et al., 2003), and even erode telomere length (Shalev et al., 2013).

These scenarios capture a variety of serious circumstances that children may experience. While not necessarily a product of criminal justice policy (and in fact, criminal courts may seek to minimize the potential harms of these situations), the justice system provides a useful way to measure their prevalence in the population and to gauge the effectiveness of broader safety net assistance programs to protect and provide for children in the U.S.

Stress from criminal proceedings. The initiation of criminal charges might trigger numerous factors that add and compound stress within the household, beyond what might have existed prior to charges being filed. These include anxiety about the resolution of the case and what potential sanctions might be applied, financial burdens associated with fines and fees stemming from court charges and correctional supervision (Harris et al., 2010; Martin et al., 2018; Finlay et al., 2022), or internal strife if charges reveal behavior that had been concealed from other household members (e.g., illicit drug use).

Research has found that ambient stress levels can negatively impact children. From fetal development (Aizer et al., 2016; Persson and Rossin-Slater, 2018) to elementary and high school (Sharkey et al., 2012; Sharkey, 2010; Ang, 2020), stress has been shown to impede physical and cognitive development and worsen educational performance (see Almond et al., 2018, for a review).

Ongoing financial security and future criminal activity. Research has also documented numerous mechanisms through which the justice system may interrupt labor market activity, jeopardize financial security, and increase long-term criminality. Mechanisms include pre-trial detention (Dobbie et al., 2018a), criminal convictions (Pager, 2003; Agan and Starr, 2017; Mueller-Smith and Schnepel, 2021), and incarceration (Mueller-Smith, 2015). In fact, research indicates that criminal justice involvement is self-perpetuating because it reduces one's ability to engage in the formal labor market, which creates further incentives to continue or increase illicit activity (Mueller-Smith and Schnepel, 2021; Deshpande and Mueller-Smith, 2022).

Financial resources have long been recognized as critical factors for child development. Birth weight (Hoynes et al., 2011), academic performance (Dahl and Lochner, 2012; Bond et al., 2021; Barr et al., 2022), mental health (Milligan and Stabile, 2011), physical health (Aizer et al., 2016), future adult criminal activity (Barr and Smith, 2023), and long-term self-sufficiency (Hoynes et al., 2016; Barr et al., 2022) have all been shown to respond to changes in available household resources during childhood. Consequently, justice contact may have long-term ramifications for the household even after the initial circumstances that led to the criminal offense are resolved due to the lasting effects on work and recidivism.

Adult or child removal from the household. Finally, the allegations associated with a criminal charge may be so severe that the composition of the household is fundamentally altered. This may include the justice-involved individual exiting the household because of incarceration, but could also reflect the dissolution of a romantic relationship due to the enhanced stress in the household or the inability for the justice-involved individual to financially provide for the family. Adult exit from the household could remove a negative influence, jeopardize continuity of care as well as financial and emotional support, or both. Using judge IVs, research on the causal effect of parental incarceration on children for the marginal convicted defendant has found positive impacts in Colombia and Ohio (Arteaga, 2021; Norris et al., 2021), no effect in Norway (Bhuller et al., 2018), and negative impacts in Sweden (Dobbie et al., 2018b).

Likewise, it may be deemed that the household is no longer a safe environment for the child. In this case, the child may be removed by child protective services and placed in the foster care system (kinship care, foster family, or group home), which research suggests can have important consequences for child well-being (Doyle, 2007; Gross and Baron, 2022).

3 Prior work on children's exposure to criminal justice

The leading estimates of child exposure to the criminal justice system come predominantly from a select group of surveys and focus almost exclusively on incarceration. Mumola (2000) and Glaze and Maruschak (2008) estimate that 2.1% of children in the U.S. in 1999 and 2.3% in 2008 have a parent in prison using the 1997 and 2007 Survey of Inmates in State and Federal Correctional Facilities.[5] Using the same survey data, paired with aggregate caseload statistics and life table methodology, which relies on strong assumptions, Wildeman (2009) estimates a higher cumulative exposure to incarceration by age 14 for White (4%) and Black (25%) children born in 1990. Enns et al. (2019) also estimate cumulative exposure using the newly fielded Family History of Incarceration Survey (FamHIS), which directly asks individuals if they have ever had a parent incarcerated in prison or jail. They find that roughly 35% of adults aged 18–29 years in 2018 and 10% of adults in their fifties report ever

[5]These statistics are inferred from reports that 55% (51.9%) of individuals in state prisons in 1999 (2007) reported having a minor child, while 63% (62.9%) of individuals in federal prisons in 1999 (2007) reported the same.

having a parent incarcerated (prison or jail).[6]

While surveys can be tailored to target a specific question, they can also suffer from reporting biases and small sample sizes, and often have poor coverage of the criminal justice population due to their low residential stability (Roman and Travis, (2004), low educational attainment (Harlow, 2003), and memberships in racial and ethnic minority groups (Carson and Anderson, 2016). Consequently, an emerging literature has sought to study child exposure to the criminal justice system using administrative data. Benefits of this approach include population-level measurement, without concerns about social desirability or attrition biases. Many of these papers, however, are based in Sweden (Hjalmarsson and Lindquist, 2012, 2013; Eriksson et al., 2016) or Denmark (Wildeman and Andersen, 2015), where integrated administrative data systems to support research and statistical reporting are among the most advanced in the world. The informativeness of these findings for U.S. policy though is limited, given the vast differences in the operations of the respective criminal justice systems (Barclay et al., 2003).

Two U.S.-focused studies, Norris et al. (2021) and Billings (2018), examine the effects of parental criminal justice events on child outcomes using administrative records in Ohio and North Carolina, respectively. Norris et al. (2021) report that 38.2% of defendants in Ohio are linked to children through birth certificates. Birth certificates unfortunately often have incomplete information, particularly for the father. For example, maternal and paternal information are observed for 99.99% and 88% of Ohio birth certificates (1972, 1984–2017) and both parents' information is observed on only 65% of Michigan birth certificates (1993–2006) (Norris et al., 2021; Almond and Rossin-Slater, 2013). Billings (2018) links school-aged children to parents identified in educational records in North Carolina using address information on school, arrest, and incarceration records and reports that 9.7% of unique children are exposed to a parental arrest during the 1998/1999 to 2010/2011 school years, with a contemporaneous exposure rate of 2% and 1% for parental arrests and incarcerations, respectively.

A remaining challenge, as Sykes and Pettit (2014) point out, is the added complexity stemming from evolving household structures and changing partnerships, particularly among those, directly and indirectly, interacting with the criminal justice system. In general, household formation and structure in the U.S. has undergone significant transformations over the past half century (Bumpass and Lu, 2000; Raley and Sweeney, 2020), with important heterogeneity by race (Lichter et al., 1992; Parker et al., 2021). Together, these have first-order implications for overall and differential under-measurement of indirect exposure

[6] There is a similar body of evidence focusing on siblings and other members of an individual's social circle who have been to prison (Lee et al., 2015; Enns et al., 2019).

among children.

4 Leveraging survey and administrative data to measure cohabitation, relationships, and justice contact

Currently, no single dataset in the U.S. captures all potential adult-minor relationships formed within their household over the course of their childhood. This project brings together a number of restricted access administrative and survey datasets available through the Census Bureau's Data Linkage Infrastructure to address this problem. While each individual dataset has its own limitations, together they provide an opportunity to measure the population in unprecedented ways.[7] Using their combined strength, we produce new population-level residence and relationship crosswalks that identify where each individual in the U.S. lives in a given year, and with whom they share familial and coresidency relationships. With intergenerational linkages identified, we leverage CJARS to track several forms of exposure to the justice system. An overview of the data, linkage processes, sample restrictions, and measurement concepts is provided below; detailed information on the construction and performance of our residency and relationship crosswalks can be found in Appendix B.[8]

The residential crosswalk seeks to establish the best-known address for every individual in the U.S. on an annual basis. It incorporates both administrative sources like IRS tax filings and household survey data like the decennial censuses.[9] When multiple addresses are identified for an individual in a given calendar year, priority is given first to addresses from Census Bureau surveys, then from tax records, and then from public program data.

The residence crosswalk functions as the "backbone" of the relationship crosswalk. First,

[7]For example, information about dependents from tax returns is only available for individuals who file a tax return. Similarly, public assistance caseload data is only available for low-income individuals who participate in these programs. Decennial census data is comprehensive, but only available every ten years.

[8]Person-level data are linked using the Census Bureau's Protected Identification Key (PIK), which are assigned to records using the Person Identification Validation System (PVS) (Wagner and Lane, 2014). While there is some non-random selection in PIK assignment (Bond et al., 2014), this project minimizes possible linkage bias by combining data from many sources. Over 90% of CJARS IDs with more than one record receive a PIK through the PVS system, and 75% of IDs with only one occurrence (Finlay and Mueller-Smith, 2020).

[9]We harvest residential addresses from the following data sources: decennial censuses (2000, 2010), American Community Survey (2001–2018), IRS Form 1040 tax filings (1969, 1974, 1979, 1984, 1989, 1994, 1995, 1998–2018 tax years), IRS Form 1040 electronic tax filings (2005, 2008–2012), Department of Housing and Urban Development program data (Longitudinal PIC/TRACS: 1995–2016, 2018; PIC: 2000–2014; TRACS: 2000–2014), Centers for Medicare and Medicaid Services enrollment data (EBD: 2000–2017; MSIS: 2000–2014), Indian Health Service enrollment data (1999–2017), and the Master Address File-Auxiliary Reference File (2000–2018).

for each year, all coresident individual pairs are identified. Where possible, these cohabiting relationships are further delineated into specific relationship types based on available information.[10] Because of the limited temporal coverage where we can effectively link children to coresident adults, we focus our analysis on the cohort of children born between 1999 and 2005 to measure exposure to parental and other potential caregiver criminal justice involvement (see Appendix Figure A1 for sample composition descriptives).[11]

Figure I summarizes the performance of the crosswalks for all children, and by racial subgroup. Overall, we are able to successfully link 97% of our focal children to female potential adult caregivers and 95% to male potential adult caregivers; furthermore, we can identify female biological parents for 90% of these children and male biological parents for 76%. We also find that 4.7%, 22%, 29%, and 46% of children are observed with a step/adopted/foster parent, extended family (grandparent/aunt/uncle), unclassified caregivers, and unclassified cohabiting adults, respectively.[12] In terms of the number of linked caregivers, we observe two or more female (male) potential caregivers for 48.3% (46.1%) of children (see Appendix Figure A3), which could be due to several factors: parents with multiple romantic partners over time, households with same-sex romantic partners, multigenerational households, or doubled-up households where multiple families share the same accommodations. Further discussion of these results, particularly by racial subgroup, can be found in Appendix B.

Adult justice system contact is measured using the 2020 vintage of CJARS, which covers 23 states with over 175 million unique events spanning multiple procedural stages of the justice system (i.e., arrest, charge, conviction, incarceration, and/or parole) with some jurisdictional coverage going back to the late 1970s. Because temporal and procedural coverage varies by jurisdiction, we restrict our analysis to children born in geographies covered by CJARS in their year of birth. Sufficient coverage is available to study criminal charges, felony charges, and felony convictions in Arizona, Florida, Maryland, Michigan, New Jersey, North Carolina, North Dakota, Oregon, Texas, and Wisconsin, which collectively cover 29.5% of the U.S. population in 2000.[13] Likewise, sufficient statewide coverage is available to study prison incarceration in Arizona, Florida, Michigan, Nebraska, North Carolina, Pennsylvania,

[10] Sources include the 2000 and 2010 decennial censuses, the American Community Survey, dependents listed on IRS Form 1040 filings, HUD program data, and the Census Household Composition Key (CHCK) file that is based on Social Security Administration SS-5 applications for Social Security Numbers.

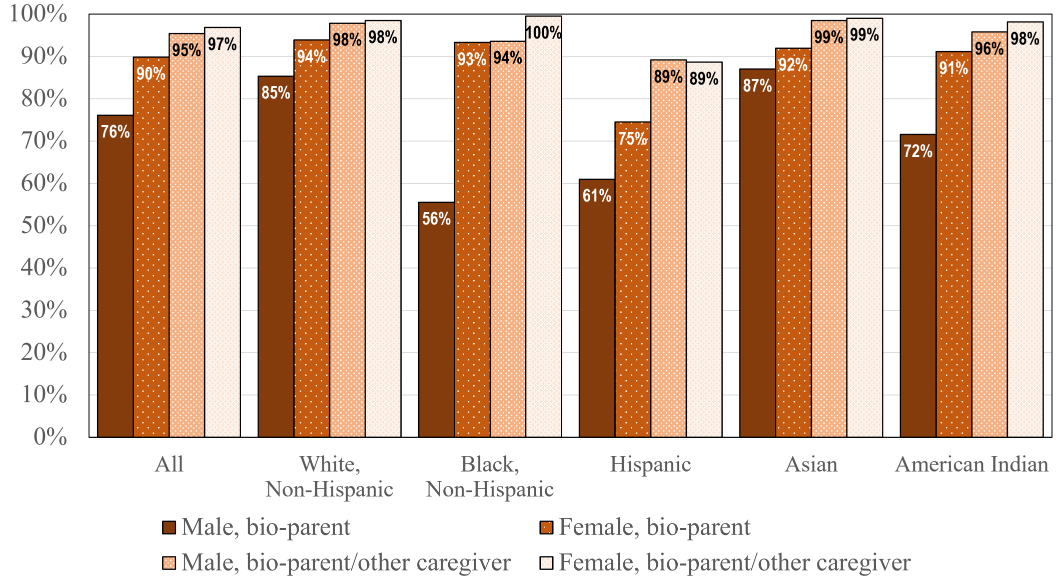
[11] The Decennial Census Digitization and Linkage project is an initiative to link microdata from the 1960–1990 decennial censuses (Genadek and Alexander, 2019). When these data become available at the Census Bureau, we will be able to investigate how exposure rates have changed over time.

[12] Appendix Figure A2 validates these relationship links by successfully replicating recent fertility estimates from the National Center for Health Statistics and the National Vitality Statistics System. Linkage performance varies by child's race and ethnicity, which may result in underestimating the true degree of indirect exposure particularly within Black and Hispanic populations.

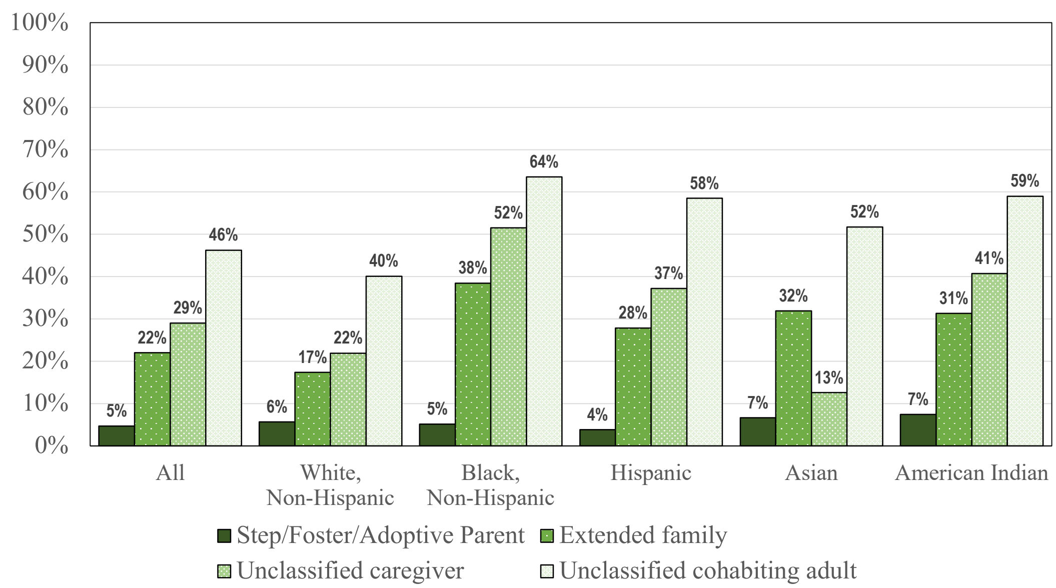
[13] Our data on misdemeanor and felony criminal charges do not include offenses classified as civil infractions like many minor traffic offenses. Instead, these represent allegations that rise to the level of a court charge.

Figure I: Share of children in 1999–2005 birth cohorts ever observed with relation type, by child race/ethnicity

A: Share of children ever observed with biological parent and other potential caregiver relationships



B: Share of children ever observed with specific potential caregiver relationships



Source: Authors' calculations from the Census Numident, Census BestRace files, CJARS, and CJARS relationship crosswalk.
Notes: This figure depicts the types of parental relationships identified for children in the Census Numident born between 1999 and 2005 from all states who are identified with a potential caregiver relationship. Potential caregivers are defined as biological parents, stepparents, adopted parents, foster parents, unclassified caregivers, grandparents, aunts/uncles, non-familial adult (cohabiting 2 or more years), and unclassified adult (cohabiting 2 or more years). The relationship can be observed at any point in time and only needs to be observed once to create the link between adult and child. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-001.

Texas, Washington, and Wisconsin, which cover roughly 30.3% of the population.[14] Even though CJARS does not have complete national coverage, Appendix Figures B3 and B4 document how CJARS states do not meaningfully differ from non-CJARS states in terms of crime and incarceration rates or in demographic and socioeconomic characteristics.

5 Estimates of child exposure to adult criminal charges, convictions, and incarceration

In this section, we report our overall findings on the extent of indirect exposure of children to charges, convictions, and incarceration by adult members of their household. To align with the previous literature, we begin by focusing on contemporaneous exposure rates stemming from justice system contact among biological parents. We then expand these definitions to account for cumulative exposure over the duration of childhood. Finally, we incorporate other potential caregivers in addition to biological parents as sources of potential exposure to arrive at our most comprehensive measures of the share of children in the U.S. who experience the justice system secondhand through adults in their households. Section 6 delves further into these estimates, examining differences in exposure by child's race, household income, adult's sex, and coresidency status at the time of exposure.

Contemporaneous exposure from biological parents. We first start with the most common estimate from the literature: child exposure to a biological parent in prison at a point in time. Specifically, we measure the probability that a minor child has a biological parent in prison in a given year using the following equation:

$$\text{Contemporaneous exposure} = \frac{\sum_{by=1999}^{2005}\sum_{i=1}^{N_{by}}\sum_{t=0}^{T_{by}} \text{CJ Exposure}_{by,i,t}}{\sum_{y=1999}^{2005} N_{by} \times T_{by}},$$

where by denotes the year of birth for a child, i references each child in the sample, N_{by} reflects the total number of children born in birth year by, t refers to the age of a child, and T_y denotes the number of years the child is in the sample—either until age 18 or until the place of birth is no longer covered by CJARS.[15] CJ Exposure$_{by,i,t}$ will equal one if child i born in year by had a biological parent (male or female) in prison when they were age t, and zero otherwise.

In Figure IIA, we document that 0.8% of children in our sample have a biological parent

[14]See Finlay and Mueller-Smith (2020) for an overview of CJARS, its codebook, and its location-specific coverage. Jail records are currently not included in CJARS, and thus not included in the exposure estimates.

[15]For example, children born in 2005 will only be in the sample for 13 years by definition.

in prison in a given year during their childhood, with 0.3% having a parent enter prison in a given year.[16] A significantly larger share of children have biological parents face criminal court proceedings, including felony convictions (0.9%), felony charges (1.2%), or any criminal charges (3.7%).

Cumulative exposure from biological parents. If children experience long-term scarring from parental involvement in the justice system, it is insufficient to know what share of children have been exposed in a given year. Instead, we need to identify how many have ever experienced exposure over the course of their childhoods. To answer this, we expand our previous measure to quantify the cumulative exposure to parental criminal justice events. Formally, we calculate the following:

$$\text{Cumulative exposure}^{\tau} = \frac{\sum_{by=1999}^{2005} \sum_{i=1}^{N_{by}} 1\left[\left(\sum_{t=0}^{\tau} \text{CJ Exposure}_{by,i,t}\right) > 0\right]}{\sum_{by=1999}^{2005} N_{by}},$$

where the numerator sums over the total number of children with a given type of exposure by age τ and the denominator divides by the total number of children born in the birth cohorts under consideration.

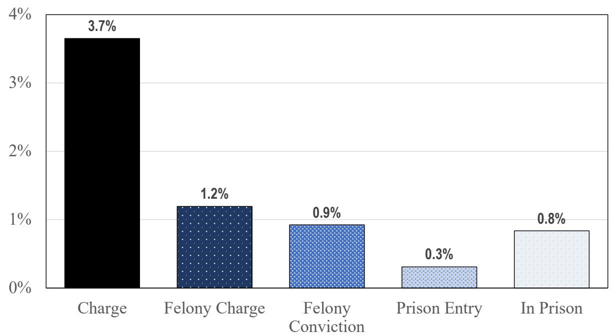
Figure IIB (solid lines) presents the share of children ever exposed by age τ (from 0 to 18) to a biological parent being in prison, convicted of a felony, charged with a felony, or charged with any criminal offense. We find that 3.6% of children experience a biological parent in prison by age 18, a 350% increase over the contemporaneous measure. Given that prison spells typically occur over multiple years, this increase observed from contemporaneous to cumulative exposure is large but relatively small in comparison with the other justice exposure measures we consider. By age 18, 9.2% of children were exposed to a biological parent's felony conviction (900% increase), 11.4% of children were exposed to a biological parent's felony charge (854% increase), and 26.0% of children were exposed to a biological parent's (misdemeanor or felony) criminal charge (613% increase).[17] Cumulative exposure

[16] The 0.8% estimate is lower than prior BJS estimates of 2.0% and 2.3% (Mumola, 2000; Glaze and Maruschak, 2008) for several reasons. First, the Survey of Inmates in State and Federal Correctional Facilities includes individuals in state *and* federal prisons, where a larger share of federal prisoners report being a parent ($\sim$ 60%). Second, the survey asks about any minor children: biologic, step, or adopted. If we instead include potential caregivers, we estimate 3.1% of children are exposed to prison, which is greater than the literature estimates as would be expected given the more expansive definition of a potential caregiver relative to the survey's question.

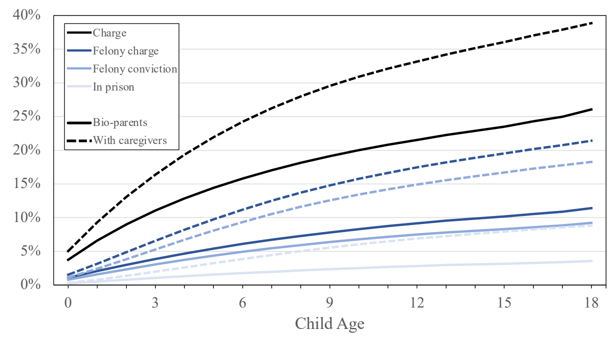
[17] Enns et al. (2019) estimate that 20% of respondents report that a parent was in jail or prison for at least one night; notably, these estimates have a steep age gradient with 34% of 18–29 year olds having a parent incarcerated compared to roughly 10% of respondents in their fifties (see Figures 2 and 4 of their paper). For children born in 1990, Wildeman (2009) and Wildeman and Andersen (2015) use life tables and the Survey of Inmates in State and Federal Correctional Facilities to estimate exposure by age 14 for children born in 1990; 25%–28% of Black children and 3.6%–4.2% of White children are exposed to parental incarceration with 7.96% (0.58%) having paternal (maternal) exposure (see Table 3 of their paper).

Figure II: Exposure to the criminal justice system and comparison of measures

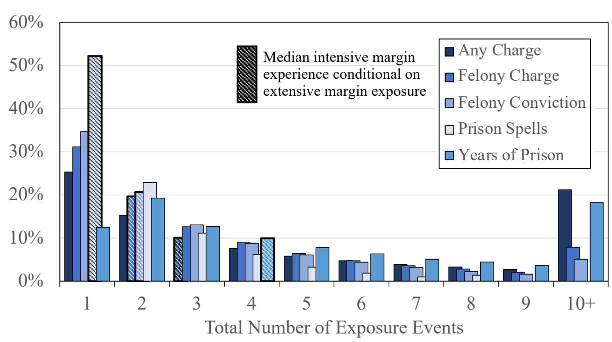
A: Contemporaneous exposure, biological parents



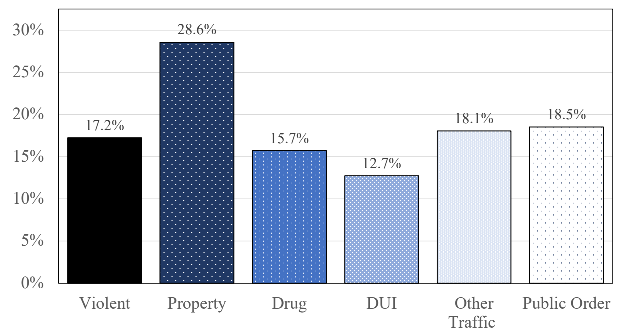
B: Cumulative exposure, biological and other potential caregivers parents



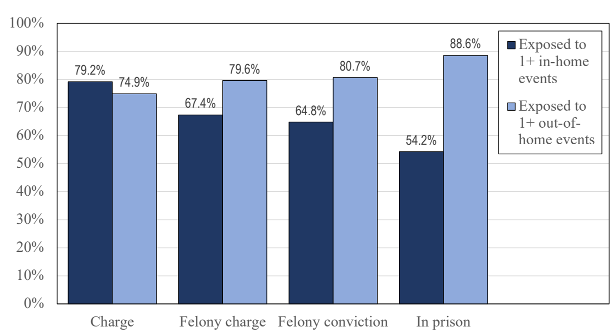
C: Intensive margin of all-source, cumulative exposure conditional on exposure of given type by 18



D: Cumulative all-source exposure by offense type by 18



E: Share of exposed minors with in versus out-of-home events by 18



Source: Authors' calculations from the Census Numident, CJARS, and CJARS relations and residency crosswalks.
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. For Panels A and B, the sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. CJARS court records cover AZ, FL, MD, MI, NJ, NC, ND, OR, TX, and WI. CJARS incarceration records cover AZ, FL, MI, NE, NC, PA, TX, WA, and WI. Potential caregivers are defined as biological parents, stepparents, adopted parents, foster parents, unclassified caregivers, grandparents, aunts/uncles, non-familial adult (cohabiting 2 or more years), and unclassified adult (cohabiting 2 or more years). For Panels C, D, and E, the sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies from birth until age 18. Distinct events are counted among children with any exposure. Thus, multiple charges filed on the same date are considered one event, and similarly for the other types of criminal justice events. The number of events is truncated at 10 events for all events *except* prison spells, which are top coded at 8. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval numbers CBDRB-FY22-ERD002-001, CBDRB-FY22-ERD002-003, and CBDRB-FY22-ERD002-009.

grows steadily through childhood. Given our focus on the extensive margin of exposure, note that the majority of first-time exposure occurs by ages 5 to 7 years old. From that point forward, cumulative exposure grows at a slower but roughly linear rate, likely reflecting both saturation among children in households with justice-involved adults and a slowdown in illicit activity as adults themselves age (see Mueller-Smith et al., 2023).

Cumulative exposure from all potential caregivers. Finally, we expand our measure of exposure to all observed potential caregivers: biological parents, stepparents, adoptive parents, foster parents, unclassified caregivers, grandparents, aunts/uncles, non-familial adults (cohabiting 2+ years) and unclassified adults (cohabiting 2+ years). To be conservative, we do not include any criminal justice involvement from other potential caregivers prior to cohabitation in our exposure measures. For example, if a stepparent has a felony conviction when the child is 3, but does not coreside with the child until the age of 6, then the child is not considered exposed to the event.[18]

Overall, we find that 8.8% of children are exposed to a potential caregiver in prison by age 18, 18.3% to a felony conviction, 21.4% to a felony charge, and 38.9% to any criminal charge. These estimates of child exposure to the criminal justice system that incorporate other adult influences in the household are much larger than those that restrict to just biological parents, with a 140% increase in exposure to prison, 99% increase in felony convictions, 88% increase in felony charges, and 50% increase in any criminal charges (misdemeanor or felony). Relative to contemporaneous exposure from biological parents, which has occupied most of the literature's attention, these broadly defined cumulative exposure measures are 958%, 1881%, 1693%, and 964% higher than single-year exposure to prison, felony convictions, felony charges, and any criminal charges, respectively.

Because we do not incorporate criminal justice contact among other potential caregivers before they initiate cohabitation in the household, the growth rate in cumulative exposure over ages 0 to 18 is more consistent year-over-year compared to exposure rates focused just on biological parents (see Figure IIB dashed line). This reflects, in part, the fact that other potential caregivers must first join the child's household and then initiate contact with the justice system before a child will be counted as "exposed."

Intensive margin of exposure. Prior results have focused on the extensive margin of exposure, referring to whether one or more events have happened in a child's household while they are minors. While this represents important new evidence, it only partially characterizes the experience of children whose households have repeated contact with the

[18] This assumption is quite strong. While children may not have direct exposure to the event, they may have indirect exposure to the justice system through ongoing community supervision requirements or direct exposure to secondary effects of justice contact, such as diminished wages from criminal records.

criminal justice system over their childhood, which we refer to as the intensive margin of exposure.

Figure IIC documents variation in the number of distinct events that children are exposed to by activity type among those who are exposed at least once. For example, multiple felony charges filed on the same date are considered one event, but felony charges filed within the same year on different dates would be two distinct events. The median *exposed* child (bars denoted with stripes) lives in a household that faces 3 criminal charges, 2 felony charges and convictions, 1 prison spell, and 4 years of adult incarceration.[19] At the high end, 21.2%, 7.9%, 5.1%, and 18.2% of exposed children live in a household with 10 or more charges, felony charges, felony convictions, and years of adult incarceration, respectively. This is important to keep in mind when interpreting Figure IIB, where we observe slowing increases in extensive margin exposure starting around age 5. While a child only experiences first-time exposure once, their household's contact with the justice system likely continues to deepen over the course of their childhood.

Offense types. In Figure IID, we disaggregate cumulative exposure rates by age 18 by the nature of the criminal charge: violent, property, drug, driving under the influence (DUI), other criminal traffic, and public order.[20] Different types of offenses provide a window into the potential living circumstances of the most vulnerable children, including exposure to violence, substance abuse, or material need as indicated by income-motivated crimes like prostitution or burglary. Property offenses are the most commonly experienced among children (29%), yet an astonishing 17% of children grow up in a household where an adult faces violent crime charges. In addition, 16% have adults in their household face illicit drug charges during childhood.[21]

Exposure during and after coresidence. A potential concern regarding the estimates presented so far is whether the observed caregiver is still in the child's life in a meaningful way at the time of the criminal justice exposure. We explore this in Figure IIE where we find that the majority of children at all levels had an exposure event by a current or recently coresiding adult in their household.[22] In fact, given that it is highly uncommon for an

[19]The median for each type of exposure is conditional on being exposed to the specific event type.

[20]See Appendix Table B4 for information on the most commonly occurring offenses within these broader categories.

[21]Figures A7A and A7B disaggregate this exercise by race and household income for further context into the documented racial and economic disparities in exposure to the criminal justice system. For example, roughly one in three Black and American Indian children have an adult in their household face violent crime charges, while only one in eight White children face the same. Across the household income distribution, property offenses are the most responsive, while DUIs decline the least.

[22]Recent coresidence is defined as the adult and child being observed living together in the year of the event or either of the two years prior. See Appendix Figure A4 for detailed information on how these rates evolve over ages 0 to 18, for biological parents and all potential caregivers.

individual to receive a prison sentence for their first criminal charge, it is likely that the subset of children with exclusively "out-of-home" exposure to severe outcomes like prison, also had less severe "in-home" events that precipitated that event.[23] Regardless, because of factors like child support and ongoing social relationships, we believe tracking out-of-home events is still worthwhile and policy relevant.

6 Socioeconomic variation in exposure outcomes

In this section, we dig further into the findings of Section 5, disaggregating cumulative exposure rates by age 18 from any potential caregiver by the child's race and ethnicity, family income at birth, and the potential caregiver's sex.

Exposure by child's race and ethnicity. Stark divides emerge when disaggregating exposure rates by the race and ethnicity of children. As seen in Figure IIIA, 62% of Black, non-Hispanic (referred to as Black for the remainder of the paper) children grow up in a household where one or more potential caregivers are charged with either a misdemeanor or felony criminal offense. American Indian/Alaska Native children have a similarly high rate at 60%, and 45% of Hispanic children have a potential caregiver charged with a criminal offense. White, non-Hispanic (referred to as White for the remainder of the paper) and Asian children have high but relatively lower rates of indirect exposure to criminal charges at 32% and 17%, respectively. Exposure rates decline for more serious forms of criminal justice contact, but remain considerably high: 11%–20% of Black, Hispanic, and American Indian/Alaska Native children have a parent or other potential caregiver in prison during their childhood; corresponding estimates for White and Asian children are 6% and 2%, respectively.[24] This pattern actually reflects growing racial and ethnic disparities with the seriousness of exposure type. Likewise, exposure dosage (intensive margin) is higher among racial and ethnic minorities, even after conditioning on the extensive margin (see Appendix Figure A8).

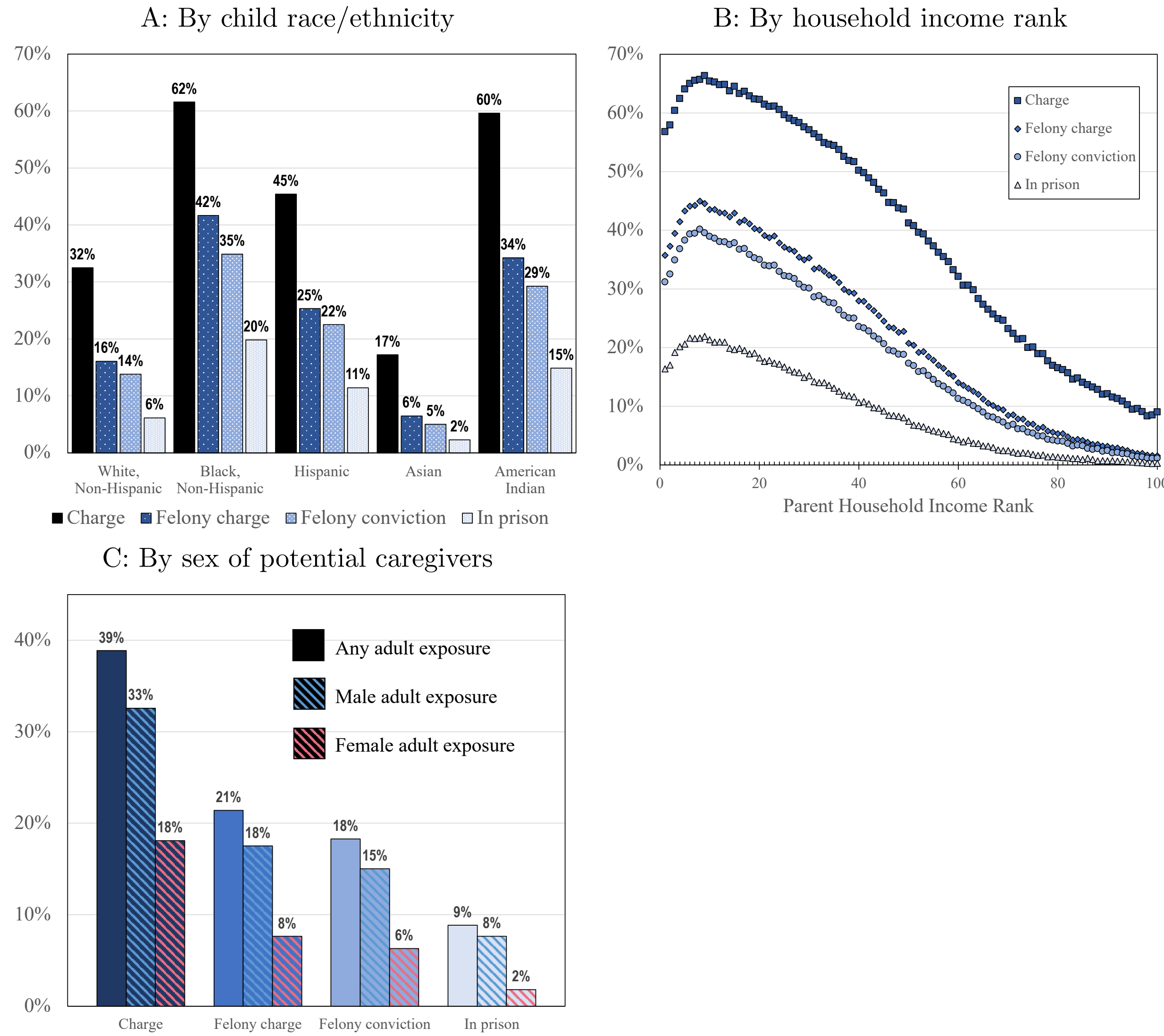
Exposure by household income rank. Figure IIIB documents changing exposure risk over the household income distribution, as measured at birth and in the following 4 years.[25]

[23]These results are consistent with statistics from the Survey of Inmates in State and Federal Correctional Facilities: 36% of fathers and 59% of mothers cohabitate with their minor children prior to incarceration (Mumola, 2000).

[24]Appendix Figure A5 provides the time path of cumulative exposure by racial subgroup. Appendix Figure A6 compares differences in cumulative exposure from biological parents by child's race. Appendix Figure A7 breaks out offense type exposure by racial subgroup and household income.

[25]We link children to the tax filings on which they are claimed as a dependent during the first 5 years of their lives and average over annual adjusted gross income. Children are ranked according to household

Figure III: Heterogeneous cumulative exposure to the criminal justice system by all potential caregivers by age 18: charge, felony charge, felony conviction, incarceration



Source: Authors' calculations from the Census Numident, Census BestRace files, CJARS, CJARS relations and residency crosswalks, and IRS Form 1040s (1999–2009 tax years).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies from birth until age 18. Average exposure by age 18 is depicted for children across race/ethnicity (Panel A), income percentile bins (Panel B), and sex of adult potential caregivers (Panel C). Income percentile bins are determined using the average adjusted gross income reported on IRS Form 1040s, in which the child is claimed for the first five years. Children claimed on a form with negative AGI or never claimed in the first five years are not included in the sample. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval numbers CBDRB-FY22-ERD002-001 and CBDRB-FY22-ERD002-003.

We observe a strong income gradient with regard to indirect criminal justice exposure by a potential caregiver, which is consistent with prior work suggesting parental criminal justice contact inhibits social mobility along a range of outcomes, including the child's own likelihood of adult incarceration (Chetty et al., 2018).[26] Children born in households at the 10th percentile of income experience exposure rates roughly 60–190% higher than children born at the 50th percentile of household income, and 440–2950% higher than children born at the 90th percentile of household income. While exposure rates for any charges remain non-zero at slightly below 10 percentage points at the very top of the income distribution, no more than 0.3–3.2% of children at or above the 90th income percentile experience exposure to felony charges, felony convictions, or incarceration.

Exposure by sex of potential caregiver. Figure IIIC depicts the cumulative exposure rates by age 18 by the sex of the potential caregiver. The vast majority (over four-fifths) of children with indirect exposure (at all levels of severity) experience a male potential caregiver having contact with the justice system. Many children are also exposed by female potential caregivers; in fact, across all types of measured exposure, 13–18% of exposed children are exposed exclusively by female adults in their household. But with increasing severity of contact, the share exposed by both male and female potential caregivers declines and the share exposed by exclusively male potential caregivers increases. For instance, 80% of prison exposure comes exclusively from male potential caregivers, while only 53% of criminal charge exposure comes exclusively from male potential caregivers.[27]

income within birth year, and exposure is calculated within individual percentiles. Income is imputed to zero in years the child is not claimed. Children never claimed or claimed on a tax filing with negative income in any year are excluded.

[26] At the very bottom of the income distribution, there is a reduction in exposure rates. This is driven by very low-income children having fewer associated tax filings and therefore fewer child-adult linkages made (see Appendix Figure A9). Appendix Figure A10 reproduces the income gradient in Figure IIIB separately by child's race and ethnicity. While it is true that all subgroups exhibit a gradient, there also remains consistent gaps of 10–20 percentage points between minority children and White children conditional on household income. Interestingly, Hispanic children begin with lower exposure rates than White children, which is reversed by the 40th percentile of household income.

[27] Appendix Figure A6 shows similar qualitative patterns when restricting to just exposure from biological parents. For comparison, Wildeman and Andersen (2015) estimates that 7.96% and 0.58% of children born in 1990 are exposed to a paternal or maternal imprisonment by the age of 14. Additional results by child race and potential caregiver sex are available in Appendix Figure A11.

7 Variation in exposure definitions and childhood outcomes

So far we have documented unprecedentedly high rates of indirect exposure of children to the U.S. criminal justice system through parents and other coresident adults in their households; for example, close to two out of three Black children grow up in households where an adult has faced criminal charges during their childhoods. But one might ask whether we have significantly diluted the pool of meaningful events that children experience by broadening the definition of exposure, and whether policymakers should worry about these new measures.

To explore this concern, we evaluate how the correlation of exposure with various measures of childhood well-being varies based on the underlying definition of what is counted. To accomplish this, we merge contemporaneous and cumulative exposure statuses over time to individual observations from children (ages 0 to 18) in respondent households from the 2005 to 2018 waves of the American Community Survey (ACS). We use the same exposure information built using the microdata previously discussed and link at the individual-level to integrate a range of well-being measures.[28] The outcomes we consider include: household-level variables—a child's household poverty status and whether a grandparent has primary responsibility for their care; and human capital development measures—whether the child is behind in school given their age and whether they have difficulty concentrating, remembering, or making decisions as a result of a mental or emotional condition.

Since whether a child is exposed likely reflects pre-existing differences in households that contribute to child outcomes ($Y_{i,t}$), we estimate the correlation between survey-year biological parent exposure ($\text{Bio}_{i,t}$), survey-year non-biological parent exposure ($\text{Other}_{i,t}$), pre-survey biological parent exposure ($\text{Bio}_{i,\tau<t}$), and pre-survey non-biological parent exposure ($\text{Other}_{i,\tau<t}$) controlling for a range of observable characteristics: a third-order polynomial in household income at birth ($\phi(Inc_i)$), age-at-survey fixed effects (γ_a), fully saturated sex-by-race/ethnicity fixed effects ($\gamma_{r,s}$), survey-year fixed effects (γ_t), place-of-birth fixed effects (γ_g), and year-of-birth fixed effects (γ_{by}).[29] Our estimating equation is as follows:

$$Y_{i,t} = \beta^1 \text{Bio}_{i,t} + \beta^2 \text{Other}_{i,t} + \beta^3 \text{Bio}_{i,\tau<t} + \beta^4 \text{Other}_{i,\tau<t} + \phi(Inc_i) + \gamma_a + \gamma_{r,s} + \gamma_t + \gamma_g + \gamma_{by} + \epsilon_{i,t}.$$

To the extent that omitted variables bias contaminates our regression coefficients, one would expect this to lead to relatively worse correlations for contemporaneous events, events asso-

[28]To avoid confusion, our exposure variables in this exercise do not reflect cohort-level exposure, but instead whether that specific child respondent to the ACS had a parent or other potential caregiver involved in the justice system in or before the year of their survey response. An adult in the household would complete the ACS and respond to the questions for the child, including schooling information and cognitive difficulty.

[29]In addition, standard errors are clustered by the commuting zone of birth. Regressions are weighted by ACS person weights. Household income at birth is measured in the same way as described for Figure IIIB.

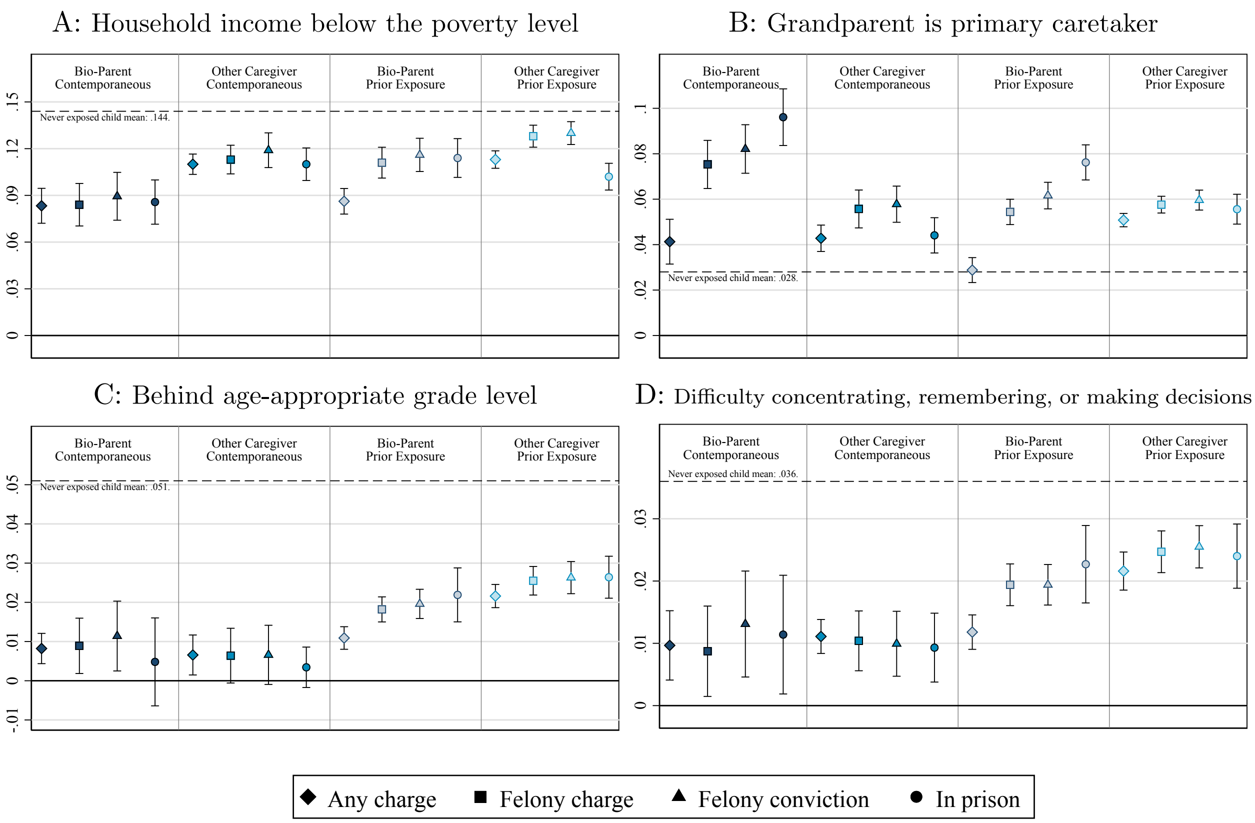
ciated with biological parents, and incarceration spells. For example, children growing up in households with biological parents who go to prison likely have more unobserved factors that inhibit their growth and development compared to children with less serious, less direct, and less recent forms of exposure (e.g., their coresiding uncle who was once charged with possession of marijuana when they were two years old).

Figure IV plots the estimated coefficients between child outcomes and contemporaneous (in the survey year) and cumulative (prior to the survey year) criminal justice exposure for each of the four event types (charge, felony charge, felony conviction, and prison) for biological parents and other potential caregivers. The estimated relationship between exposure and household poverty status (Panel A) is remarkably similar regardless of the specific exposure definition. Whether exposure reflects charges or incarceration, biological parents or other potential caregivers, or current or past events, the estimates consistently fall in the range of 60 to 90 percent of the never-exposed child mean, with many of the coefficients being statistically indistinguishable. These findings are consistent with, although obviously not definitive causal proof of, the hypothesis that part of the negative economic impacts of the justice system on families operates through the channel of scarring effects of criminal records. Whether grandparents are identified as the child's primary caregiver (Panel B), however, does seem to be both more intimately connected to the most serious forms of justice contact like felony convictions and incarceration, and be most strongly associated with the justice involvement of biological parents over other potential caregivers. This clear pattern aligns with the legal processes in place for child welfare investigations, child removal, and resulting kinship care placements.

The next two panels show a strikingly similar pattern of evidence regarding human capital formation during childhood. Whether the child is behind in age-appropriate grade level (Panel C) or is reported to have difficulty concentrating, remembering, or making decisions resulting from a mental or emotional condition (Panel D), the strongest negative correlations are associated with cumulative rather than contemporaneous exposure to the justice system. Whether the source originated from a biological parent or another adult in the household, or whether the type of exposure was incarceration or something less serious, the estimated relationships are quite similar.

Overall, we interpret this body of evidence to show that policymakers should carefully consider our more broadly defined measures of child indirect exposure to the U.S. justice system. Whether the result of selection in justice involvement or a consequence of justice involvement, these new measures correctly identify a substantially larger population of vulnerable children.

Figure IV: Correlations between indirect exposure and child outcomes



Source: Authors' estimates from the 2005–2018 American Community Survey (outcomes), Census Numident (year of birth, sex, mortality), Census BestRace files (race/ethnicity), CJARS (potential caregiver exposure and child adult charges), and CJARS relationship crosswalk (identify potential caregivers and measure child fertility).
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. Estimates along with 95% confidence intervals are shown. All regressions with controls include fixed effects for the county of birth, birth year, and race/ethnicity interacted with gender along with a third-order polynomial for average adjusted gross income in the first five years of the child's life, as measured by IRS Form 1040. Standard errors are clustered by the commuting zone of birth. Person weights provided by the American Community Survey are used. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth at the time of survey response (0–18) with the place of birth still covered or year 2018. Contemporaneous exposure to an event is measured in the year of the survey, and prior exposure is measured from birth until the year prior to the survey response. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-009.

8 The long-term effects of growing up in high-exposure areas

Our final empirical analysis examines how children who grow up in areas with a relatively more expansive criminal justice system fare when reaching young adulthood. To accomplish this task, we first document substantial geographic variation in indirect exposure among children across U.S. counties. With that in hand, we employ a "movers analysis," which seeks to eliminate many candidate sources of confounding variation by focusing on the subsample of children who are born in one place but move during their childhoods into higher and lower exposure areas (Chetty et al., 2013; Finkelstein et al., 2021; Chetty and Hendren, 2018a,b). This work is complemented by two additional empirical exercises, the first focusing on the duration of living in a high-exposure county among movers and the second restricting variation to differences in exposure duration among biological siblings.

County-level variation in exposure. As previously discussed, geographic coverage by procedural domain varies within CJARS. To maximize potential comparisons, we construct an index of intensity of criminal justice child exposure at the county level that leverages both felony conviction and incarceration exposure rates for children born in the 1999–2005 cohorts. We first construct race (r) by county-of-birth (g) z-scores for both indirect felony conviction and incarceration exposure rates (i.e., mean of zero, standard deviation of one). We then average the z-score variables where both are available, or substitute in whichever z-score component is available when one is missing due to geographic coverage. In the final step, we rescale the composite z-scores into the unit interval by subtracting off the minimum value and dividing by the distance between the max and min values. We create the index using the following equations:

$$\text{Exposure index}_{g,r} = \frac{Z_{g,r} - min(Z)}{max(Z) - min(Z)}, \text{ where}$$

$$Z_{g,r} = \begin{cases} \mathrm{Z}^{\text{Inc}}_{g,r} & \text{if missing } \mathrm{Z}^{\text{Fel Conv}}_{g,r} \\ \mathrm{Z}^{\text{Fel Conv}}_{g,r} & \text{if missing } \mathrm{Z}^{\text{Inc}}_{g,r} \\ (\mathrm{Z}^{\text{Inc}}_{g,r} + Z^{\text{Fel Conv}}_{g,r})/2 & \text{otherwise} \end{cases},$$

$$Z^{\text{Inc}}_{g,r} \equiv \frac{\text{Exposure}^{\text{Inc}}_{g,r} - \text{Exposure}^{\text{Inc}}}{\text{st dev}\big(\text{Exposure}^{\text{Inc}}\big)}, \quad \text{and} \quad Z^{\text{Fel Conv}}_{g,r} \equiv \frac{\text{Exposure}^{\text{Fel Conv}}_{g,r} - \text{Exposure}^{\text{Fel Conv}}}{\text{st dev}\big(\text{Exposure}^{\text{Fel Conv}}\big)}.$$

While it would be preferable to avoid missing values, among the 404 counties where we observe both types of exposure, there is a tight correlation (see Appendix Figure A12), which suggests that this is a reasonable empirical strategy to maximize geographic coverage.

Figure V shows a map of the geographic variation we observe in the modeled index as well as its relationship with county-level measures of non-modeled felony conviction and incarceration exposure rates. Overall, we observe substantial geographic heterogeneity. Children born in the 75$^{\text{th}}$ versus 25$^{\text{th}}$ exposure percentiles have a 9.5 and 6.8 percentage point (78% and 156%) higher likelihood of being exposed through adults in their household to a felony conviction and incarceration event, respectively. At the extremes, there are 50 and 35 percentage point gaps in felony conviction and incarceration exposure rates for children growing up in counties at the very top of the index compared to those at the bottom of the distribution.

As shown in the map, some of this is driven by between-state variation. Texas and Florida exhibit substantially higher exposure rates compared to New Jersey and Washington. That said, there are also clear differences within states (e.g., Miami-Dade versus Tampa, Newark versus Camden, or Dallas versus San Antonio). Such differences do not appear solely driven by variation in the racial composition across counties, as we observe similar geographic patterns when restricting to just White or Black children (see Appendix Figure A13). Together, these highlight the fundamental role that state and local actors/policymakers play in the functioning of the highly decentralized U.S. justice system.

Movers analysis. To assess whether geography exerts a plausibly causal influence on exposure to the justice system and what impact that may have on the long-term trajectories of children, we turn to a movers analysis. The thought experiment behind this exercise is to track two children, born in the same original county, but one moves to a high-exposure county and the other moves to a low-exposure county. Does the child who moves to a high-exposure county go on to have a higher likelihood of an exposure event? Do we observe differences in their adult outcomes?

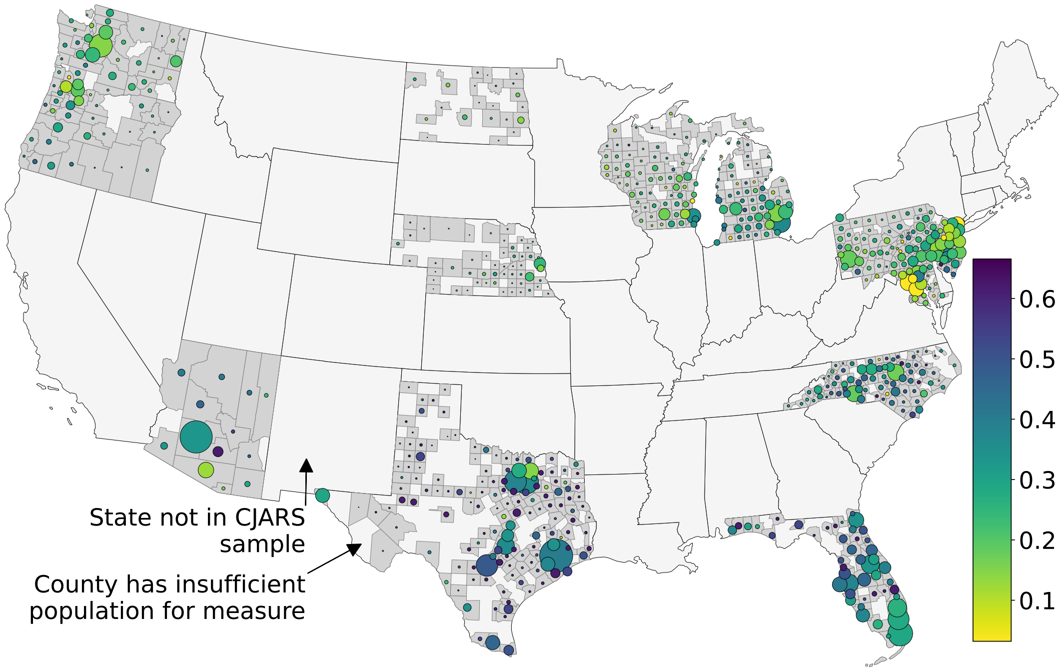
To estimate the effect of growing up in places with higher rates of justice exposure, we focus on children who move to a new commuting zone after birth exactly once by age 17, following Chetty and Hendren (2018a,b). We expect earlier moves to have a stronger effect due to longer exposure during childhood. Our estimating equation is the following:

$$Y_{i,g,r,c} = \beta \text{Exposure index}_{c,r} + \delta X_c + \phi(Inc_i) + \gamma_{r,s} + \gamma_{by} + \gamma_{g,r} + \epsilon_{i,c},$$

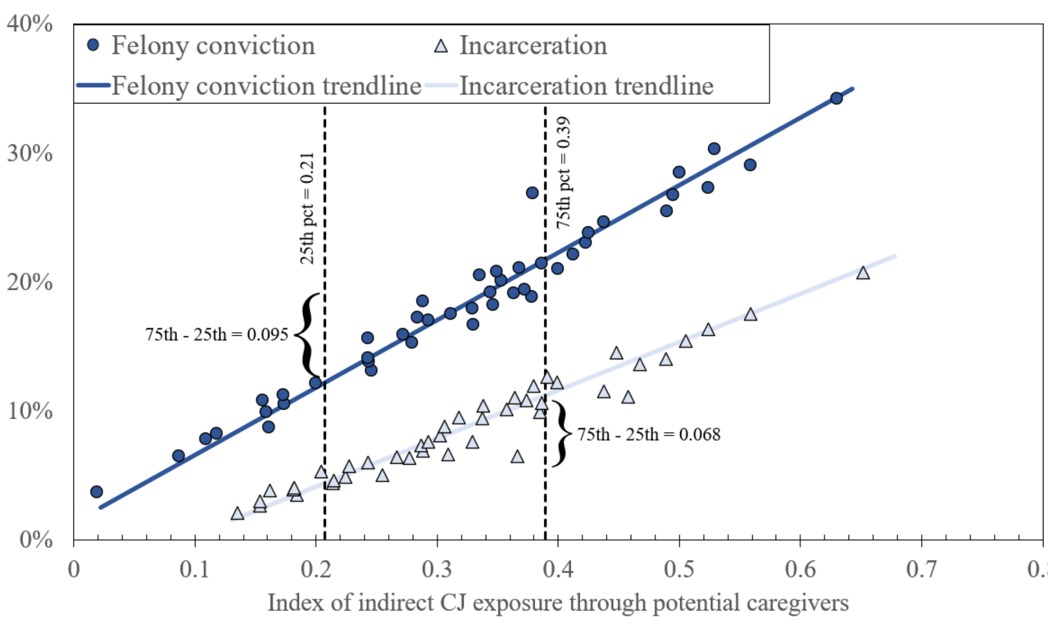
where subscript g represents the county of birth and subscript c represents the destination county. The focal coefficient is β, which measures the correlation of outcome Y with destination county c's prevailing exposure index, controlling for other county characteristics X_c. We also include for a third order polynomial in household income at birth ($\phi(Inc_i)$), race by sex fixed effects ($\gamma_{r,s}$), birth year fixed effects (γ_{by}), and county of birth by race fixed effects ($\gamma_{g,r}$). To maximize our sample, we consider all children in the U.S. who move into

Figure V: County variation in degree of child indirect exposure rates

A: Map of county-level index variation



B: Relationship between exposure index and rates of felony convictions and prison incarceration



Source: Authors' calculations from the Census Numident, Census BestRace files, CJARS, and CJARS relations and residence crosswalks.

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies. Map markers are sized according to 2021 Census Bureau county total population estimates. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-0138.

CJARS-covered states, not just those who are born in our covered jurisdictions.

Including X_c in the regression helps us evaluate whether the impacts of moving to a high-exposure county may be in fact the product of the justice system itself, or alternatively the result of other county policies or characteristics that happen to be correlated with exposure rates. The county characteristics we include, drawn from Chetty et al. (2014), are child upward economic mobility, Metro area indicator, fraction Black, racial segregation, income segregation, fraction with commute less than 15 minutes, local tax rate, school expenditure per student, manufacturing employment share, growth in Chinese imports 1990–2000, migration inflow rate, migration outflow rate, and fraction foreign born. With the exception of the child upward economic mobility measure, we focus on variables that we believe may not themselves be potentially impacted by the justice system (e.g., education spending is included while child poverty rates are excluded). The correlation matrix between the county covariates and the exposure index is shown in Table A1.

Table I shows the first-stage relationship between moving into a higher exposure index county and experiencing an indirect exposure event. Among moving children, those who go to places where households have higher likelihoods of being justice-involved are significantly more likely to have new post-move indirect exposure incidents stemming from adults in their household on all observed justice events: criminal charges, felony charges, felony convictions, and incarceration. The magnitude of these coefficients represent 42% and 35% of the observed felony conviction and incarceration exposure gaps for children born in counties at the top and bottom of the index distribution. By construction, we should expect these effects to be less than 100% since our sample of moving children spends significantly less of their childhoods in the destination counties compared to children actually born in these counties and thereby have fewer years to accumulate indirect exposure in these new environments. This exact dynamic is confirmed in the even columns of Table I, where children who move at younger ages are more likely to have new post-move exposure incidents after moving to a higher index county.

Unfortunately, the birth cohorts in our focal sample are too young to observe as adults.[30] Instead, we turn to the slightly older 1990 to 1996 birth cohorts, who we can observe at least through their mid-twenties.[31] The assumption we make by using this substitution is that the

[30]In Section 7, we consider child outcomes available in the ACS. While bringing those outcomes into the movers analysis would be quite interesting, the samples become too small when restricting to post-move ACS responses in CJARS-covered states, especially since some of our focal birth cohorts only reach age 13 in the most recently available ACS data.

[31]Our ability to measure residences on an annual basis becomes much better starting in the year 1998, which means that for some children born between 1990 and 1996 we will know they have moved by age 8 but not exactly when. Thus, in the analysis, age at the time of the CZ move is grouped together for children moving between the ages of 1 through 8, 9 through 12, and 13 through 17.

Table I: The impact of moving to a high-exposure county on child's indirect exposure through biological parents or coresident adults

	Criminal charge	Criminal charge	Felony charge	Felony charge	Felony conviction	Felony conviction	Incar-ceration	Incar-ceration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exposure index	0.235***		0.203***		0.222***		0.131***	
	(0.030)		(0.019)		(0.016)		(0.012)	
Move $\leq 8 \times$ Index		0.340***		0.274***		0.293***		0.173***
		(0.034)		(0.022)		(0.019)		(0.014)
Move 9-12 $\times$ Index		0.104***		0.136***		0.166***		0.108***
		(0.036)		(0.024)		(0.021)		(0.017)
Move 13-17 $\times$ Index		0.079**		0.065***		0.066***		0.023**
		(0.033)		(0.024)		(0.019)		(0.011)
Observations	364,000	364,000	364,000	364,000	364,000	364,000	377,000	377,000
Sample mean	0.271	0.271	0.140	0.140	0.118	0.118	0.059	0.059

Notes: Source: Authors' estimates from CJARS (county-level potential caregiver exposure and household adult criminal justice events), IRS 1040 tax records (control variable for income), CJARS relationship crosswalk (identify potential caregivers), Census BestRace files (race/ethnicity), and the Census Numident (year of birth, sex).

The sample is individuals born in 1999-2005 that change CZs once by age 17 into a CJARS-covered county, as measured in the CJARS residence crosswalk. The index of CJ exposure is a standardized measure of county-level felony conviction and incarceration exposure normalized between 0 and 1. Exposure outcomes are measured for linked adults during the post-move period using CJARS. Each regression controls for sex by race, county of birth by race, year of birth fixed effects, and a cubic polynomial of household income at the time of birth (average Form 1040 AGI over the first five years). All controls are interacted with indicators for the timing of the move, as measured in three categories ($\leq$8, 9-12, 13-17). Standard errors are clustered at the CZ of birth. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-0235. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

geographic variation measured for later birth cohorts still provides meaningful identifying information for mover children born about a decade earlier. We measure adult outcomes at age 26, including ever having received an adult criminal charge, employment and wages at age 26, teen parenthood, and mortality.[32] Together, these provide a broad array of outcomes to measure well-being in early adulthood.

Table II shows the results of this exercise. For each outcome, the first two columns show the overall effect of moving into a high-exposure county without and with controls for county characteristics. While not definitive proof, our findings show a remarkably stable relationship whether we do or do not include this vector of county covariates. This is evidence that we interpret as consistent with a potential causal impact of the justice system on children's life cycle outcomes. After controlling for other destination county traits, we find that moving into a high-exposure county significantly worsens future adult outcomes for children. For example, moving into a 75th versus 25th percentile county, which would raise the likelihood of exposure to a post-move felony conviction or incarceration by 4.0 percentage points (34%) and 2.4 percentage points (40%), respectively, increases the likelihood that a child has their own criminal justice involvement as an adult by 1.1 percentage points (8%), reduces employment by 0.9 percentage points (-1.1%), increases the likelihood of teen parenthood by 1.9 percentage points (26%), and increases the likelihood of death by age 26 by 0.05 percentage points (6.4%). Furthermore, wages at age 26 decline by approximately 13 percent over this same interval, suggesting significant movement on the intensive margin of work.

Similar to the first-stage exercise, we find that children who moved at earlier ages are most impacted by the exposure rate of their destination county. In fact, the estimated relationship between destination exposure rates and adult outcomes for young movers (ages 1–8) is roughly twice the size for all outcomes compared to teenage movers (ages 13–17). This suggests that the poor adult outcomes we observe are not simply a consequence of an unproductive or unhealthy adult environment, but also of how that context contributes to child development specifically. Although we lose some precision due to the drop in sample size, this same qualitative pattern is observed for most outcomes when including biological sibling fixed effects, where identification is based solely on the relative age at the time of the move within a family unit, holding fixed the destination county and underlying household circumstances or reason for the move.[33]

Figure VI disaggregates this exercise by child's race/ethnicity, child's gender, and household income at birth. Low-income, Hispanic, and American Indian children's post-move exposure

[32]For later birth cohorts in this sample, we use the oldest observed age given available data, which makes a small share of our observations younger than 26.

[33]By definition, the sibling fixed effect specification restricts to children with at least one sibling. Additionally, we exclude the small proportion of children matched to more than 10 siblings for this specification.

Table II: The impact of moving to a high-exposure county on adult outcomes

	Criminal charge by age 26				W-2 employment at age 26				IHS(W-2 wages at age 26)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Exposure index	0.093***	0.062***			-0.054***	-0.052***			-0.85***	-0.74***		
	(0.014)	(0.014)			(0.006)	(0.006)			(0.08)	(0.08)		
Move $\leq 8 \times$ Index			0.080***	0.083			-0.070***	-0.148***			-1.00***	-1.58***
			(0.015)	(0.074)			(0.007)	(0.042)			(0.08)	(0.48)
Move 9-12 $\times$ Index			0.054***	0.115			-0.039***	-0.007			-0.53***	-0.32
			(0.016)	(0.090)			(0.009)	(0.048)			(0.10)	(0.54)
Move 13-17 $\times$ Index			0.038*	0.159			-0.037***	-0.011			-0.52***	-0.43
			(0.022)	(0.108)			(0.011)	(0.052)			(0.14)	(0.55)
Observations	814,000	779,000	779,000	98,500	1,497,000	1,412,000	1,412,000	228,000	1,497,000	1,412,000	1,412,000	228,000
Sample mean	0.133	0.137	0.137	0.115	0.852	0.851	0.851	0.863	8.93	8.92	8.92	9.10
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y		Y	Y	Y
County controls		Y	Y	Y		Y	Y	Y		Y	Y	Y
Bio sibling fixed effects				Y				Y				Y

	Teen parent				Death by age 26			
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Exposure index	0.122***	0.103***			0.0024**	0.0029***		
	(0.006)	(0.006)			(0.0010)	(0.0011)		
Move $\leq 8 \times$ Index			0.127***	0.081**			0.0044**	0.0254**
			(0.007)	(0.035)			(0.0017)	(0.0119)
Move 9-12 $\times$ Index			0.098***	0.021			0.0014	0.0192
			(0.008)	(0.042)			(0.0022)	(0.0133)
Move 13-17 $\times$ Index			0.063***	0.018			0.0017	0.0203
			(0.008)	(0.041)			(0.0026)	(0.0142)
Observations	1,497,000	1,412,000	1,412,000	228,000	1,497,000	1,412,000	1,412,000	228,000
Sample mean	0.069	0.071	0.071	0.058	0.008	0.008	0.008	0.007
Individual controls	Y	Y	Y	Y	Y	Y	Y	Y
County controls		Y	Y	Y		Y	Y	Y
Bio sibling fixed effects				Y				Y

Source: Authors' estimates from CJARS (county-level potential caregiver exposure and child's adult charges), IRS W-2 and 1040 tax records (outcome and control variable for income), CJARS relationship crosswalk (identify potential caregivers and measure child fertility), Census BestRace files (race/ethnicity), the Census Numident (year of birth, sex, mortality), and geographic characteristics from Chetty et al. (2014).

Notes: The sample is individuals born in 1990-1996 that change CZs once by age 17 into a CJARS-covered county, as measured in the CJARS residence crosswalk. The index of CJ exposure is a standardized measure of county-level felony conviction and incarceration exposure normalized between 0 and 1. Outcomes include receiving a criminal charge (CJARS), employment and the inverse hyperbolic sine transformation of wages (W-2 tax records), teen parenthood (CJARS relationship crosswalk), and mortality (Census Numident). Each regression controls for sex by race, county of birth by race, year of birth fixed effects, a cubic polynomial of household income at the time of birth (average Form 1040 AGI over the first five years), and a vector of county characteristics (where noted). All controls are interacted with indicators for the timing of the move, as measured in three categories ($\leq$8, 9-12, 13-17). Standard errors are clustered at the CZ of birth. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-0235. * p<0.1, ** p<0.05, *** p<0.01.

appears to be especially influenced by prevailing local conditions, showing above-average first-stage relationships, while high-income and Asian children show significantly lower responsiveness. All children appear negatively impacted by moving to high-exposure counties, although results for Asian children are fairly imprecise. Following the pattern in the first stage, Low-income, Hispanic, and American Indian children are most likely to go on to have their own criminal charges by age 26 when moving to a high-exposure county. For employment and earnings, low-income, White and female children appear to be most negatively impacted by prevailing local conditions. Increases in teen parenthood rates are most strongly associated with female, White, and low-income children. In contrast, our findings on early life mortality by age 26, however, appear to be largely driven by Black and male children.

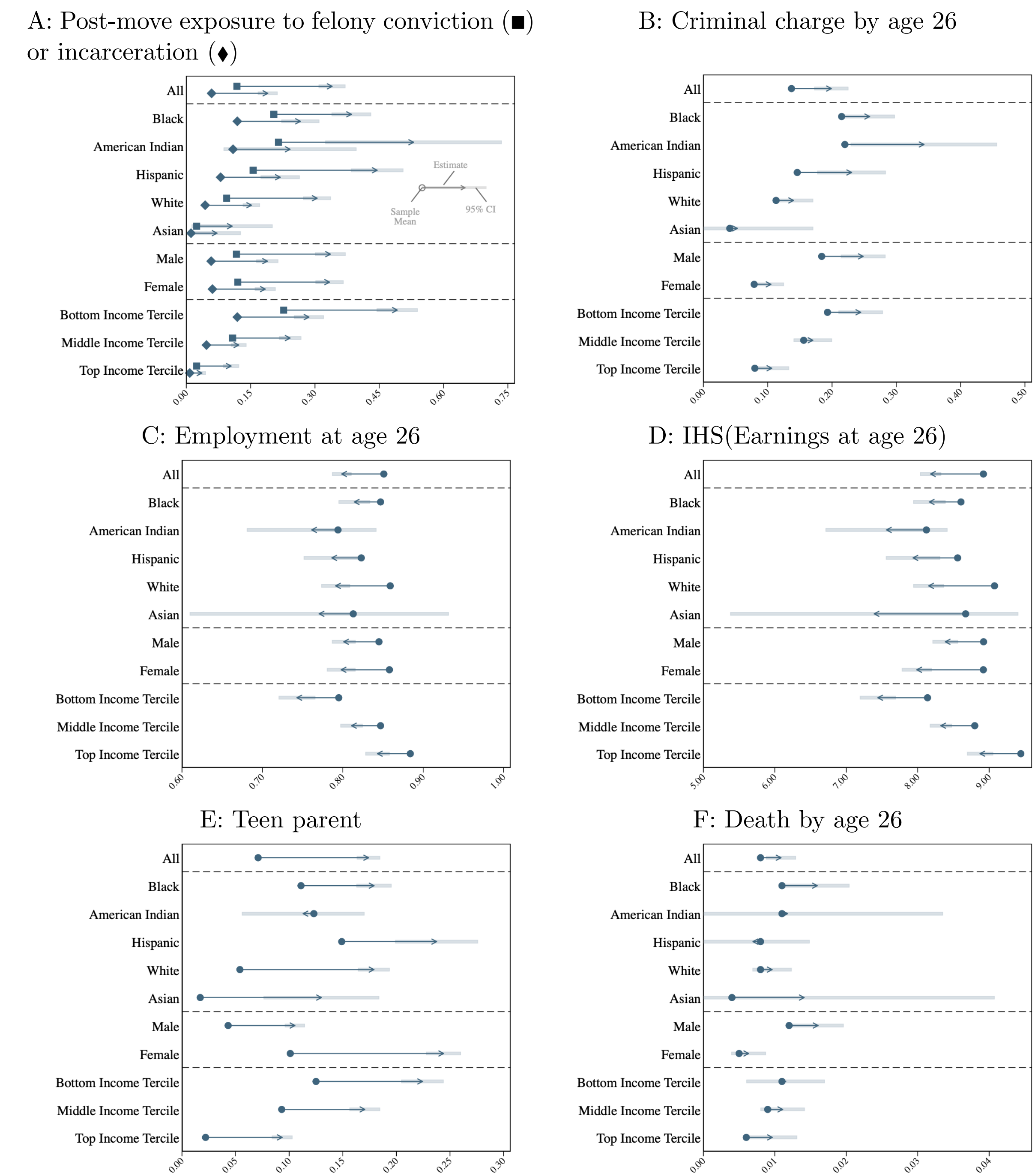
This analysis provides evidence consistent with a causal relationship between widespread household justice exposure in U.S. communities and harms to future generations that are borne out over the course of the life cycle. Given the socioeconomic and racial disparities in exposure previously discussed, the U.S. justice system could be an important factor in propagating economic inequality and racial inequities.

9 Conclusion

Despite significant, longstanding interest from researchers and policymakers, the scope and impact of indirect exposure of children to the U.S. justice system through adults in their households has been challenging to measure because of a variety of data limitations. First, it is difficult to observe the relevant caregivers over the course of a child's life, particularly in light of changing demographic trends in household composition. Second, criminal justice records are not integrated across state and local agencies, creating significant barriers to observe adult justice involvement over time and across geography. To overcome these challenges, we have built residence and familial crosswalks within the Census Bureau's Data Linkage Infrastructure that leverage restricted-access microdata from surveys, federal tax forms, and public program enrollment records, and then link them to integrated and harmonized justice records available through CJARS.

Using this new data infrastructure, we produce novel measures of indirect exposure of children through parents and adult household members to charges, felony charges, felony convictions, and incarcerations. For children born between 1999 and 2005, we find that 9% of children have had an exposure to prison, 18% to a felony conviction, and 39% to any criminal charge over the course of childhood. These prevalence rates are substantially larger than previous estimates focused primarily on parental incarceration.

Figure VI: The impact of moving to a high-exposure county, by demographic group



Source: Authors' estimates from CJARS (county-level potential caregiver exposure and child's adult charges), IRS W-2 and 1040 tax records (outcome and control variable for income), CJARS relationship crosswalk (identify potential caregivers and measure child fertility), Census BestRace files (race/ethnicity), the Census Numident (year of birth, sex, mortality), and geographic characteristics from Chetty et al. (2014)..

Notes: Coefficient plots show the sample mean, estimated coefficients on destination county exposure index among movers, and corresponding 95% confidence intervals (censored at 0 for readability). The sample is individuals born in 1999-2005 (A) or 1990-1996 (B–F) that change CZs once by age 17 into a CJARS-covered county, as measured in the CJARS residence crosswalk. The index of CJ exposure is a standardized measure of county-level felony conviction and incarceration exposure normalized between 0 and 1. Exposure outcomes are measured for linked adults during the post-move period using CJARS. Outcome variables are receiving a criminal charge (CJARS), employment and the inverse hyperbolic sine transformation of wages (W-2 tax records), teen parenthood (CJARS relationship crosswalk), and mortality (Census Numident). Each regression controls for sex by race, county of birth by race, year of birth fixed effects, a cubic polynomial of household income at the time of birth (average Form 1040 AGI over the first five years), and a vector of county characteristics (B–F only). All controls are interacted with indicators for the timing of the move, as measured in three categories ($\leq$8, 9-12, 13-17). Standard errors were clustered at the CZ of birth. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-0235.

We document important differences by race, which have significant implications for policies related to child well-being and persistent intergenerational inequalities. For example, Black children have the highest rates of indirect exposure to prison (20%), felony conviction (35%), felony charges (42%), and any criminal charge (62%). We document similarly high rates for American Indian/Alaska Native children, a population rarely studied, with corresponding estimates of 15%, 29%, 34%, and 60%. These estimates stand in stark contrast to those of White and Asian children, who have the lowest rates of household contact with the justice system, with 6% and 2% of White and Asian children exposed to prison and 32% and 17% of White and Asian children exposed to any charge during childhood, respectively.

To gauge whether such larger prevalences are a byproduct of expanding our inclusion criteria to less consequential shocks, we merge individual-level exposure information to ACS survey responses. We regress measures of childhood wellbeing on varying exposure definitions, and find consistent strong negative relationships with poor outcomes regardless of what criteria defined an exposure event. The resulting implication is that broader definitions, which are orders of magnitude larger, remain valuable predictors of childhood vulnerability.

Finally, we document substantial geographic heterogeneity in exposure rates, which we leverage in a movers analysis to assess the causal impact of growing up in a high-exposure area. Children who move into high-exposure counties grow up to have significantly worse lives: higher crimes rates, lower employment and earnings, higher risk of becoming a teen parent, and greater likelihood of death by age 26.

Taken together, our findings indicate that indirect exposure of children to the justice system is both widespread and potentially consequential. Given the scope of exposure and its disparate racial nature, the justice system should become a first-order concern for those interested in economic inequality, intergenerational mobility, and racial inequities in the U.S. Moreover, these results heighten the need for further research to better understand what factors have contributed to such widespread justice involvement for households with minor children and the implications for current and future generations. .

FINLAY: U.S. CENSUS BUREAU

MUELLER-SMITH: UNIVERSITY OF MICHIGAN

STREET: UNIVERSITY OF MISSOURI

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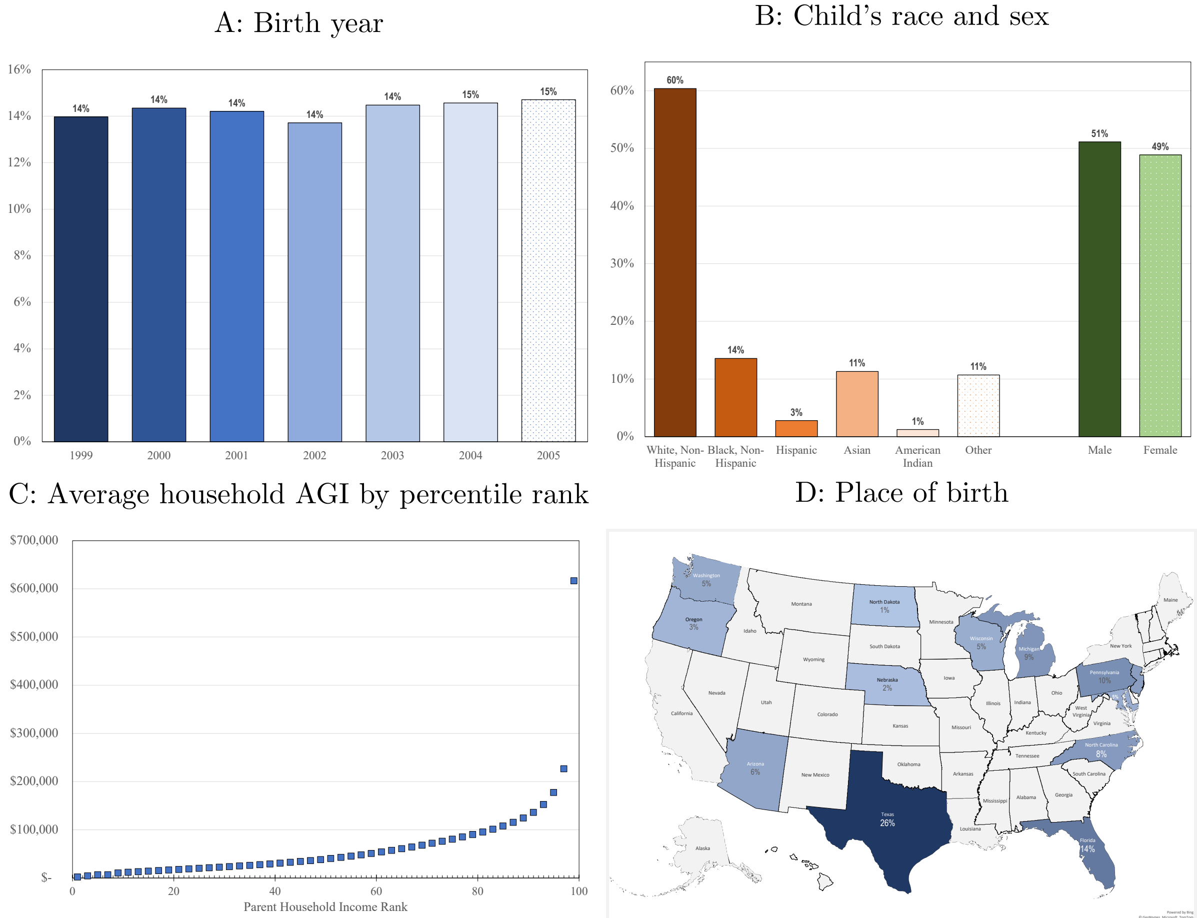
Appendix Materials for "Children's Indirect Exposure to the U.S. Justice System: Evidence from Longitudinal Links between Survey and Administrative Data"

Keith Finlay, Michael Mueller-Smith, and Brittany Street

Table of Contents

A Supplementary results

Figure A1: Composition of sample

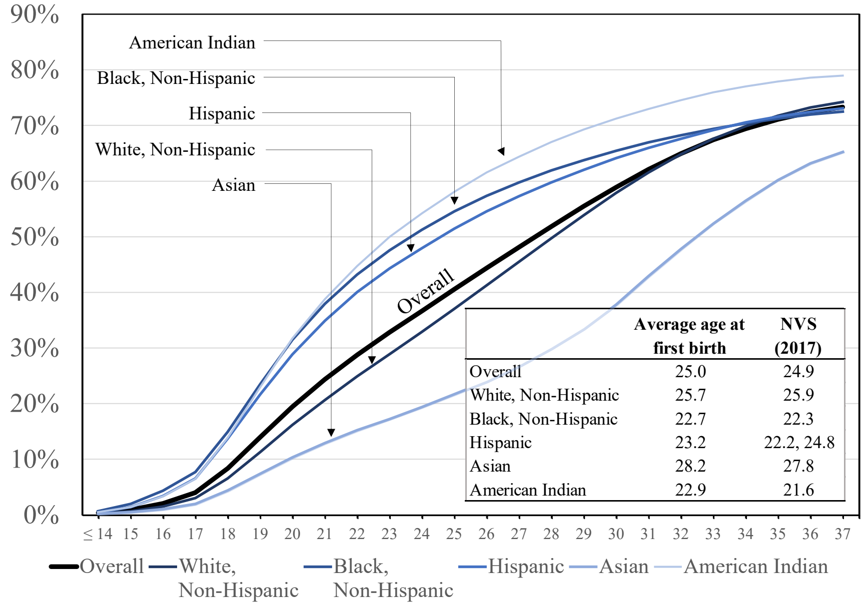


Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

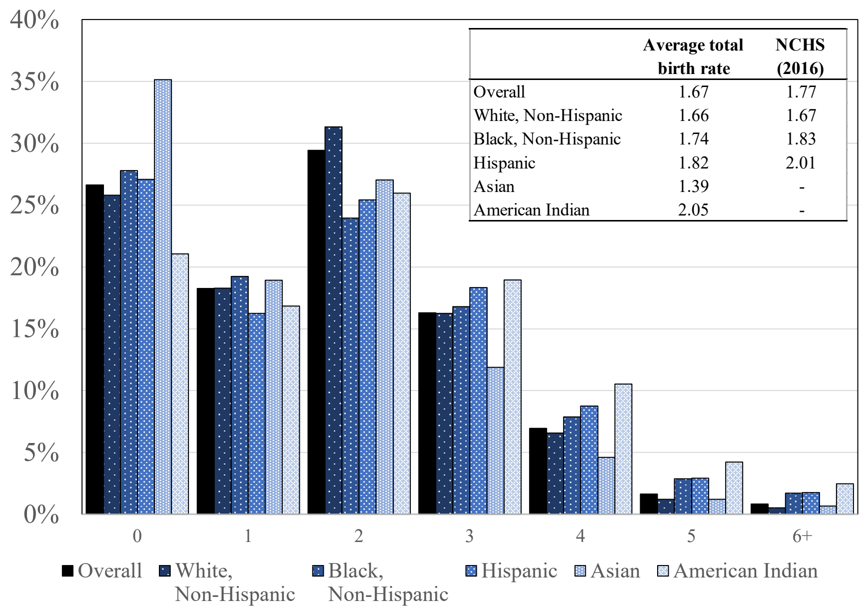
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered states during the year of birth. Child's year of birth, place of birth, and sex are measured using the Census Numident. Child's race is measured using the Census BestRace files. Average Adjusted Gross Income (AGI) is measured on the IRS Form 1040 that the child is claimed on in their year of birth and the subsequent four years. AGI is reported as zero if the child is not claimed. Children that are not claimed in their first five years of life or are ever claimed on a form reporting negative AGI are dropped from the sample in Panel C and D. Panel C and D depict average AGI, number of caregiver links observed, and the number of tax filings within the first five years for children within percentile bins as rank-ordered within birth cohorts. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-009.

Figure A2: Life cycle fertility for females born in 1981 by race

A: Share with observed birth by age



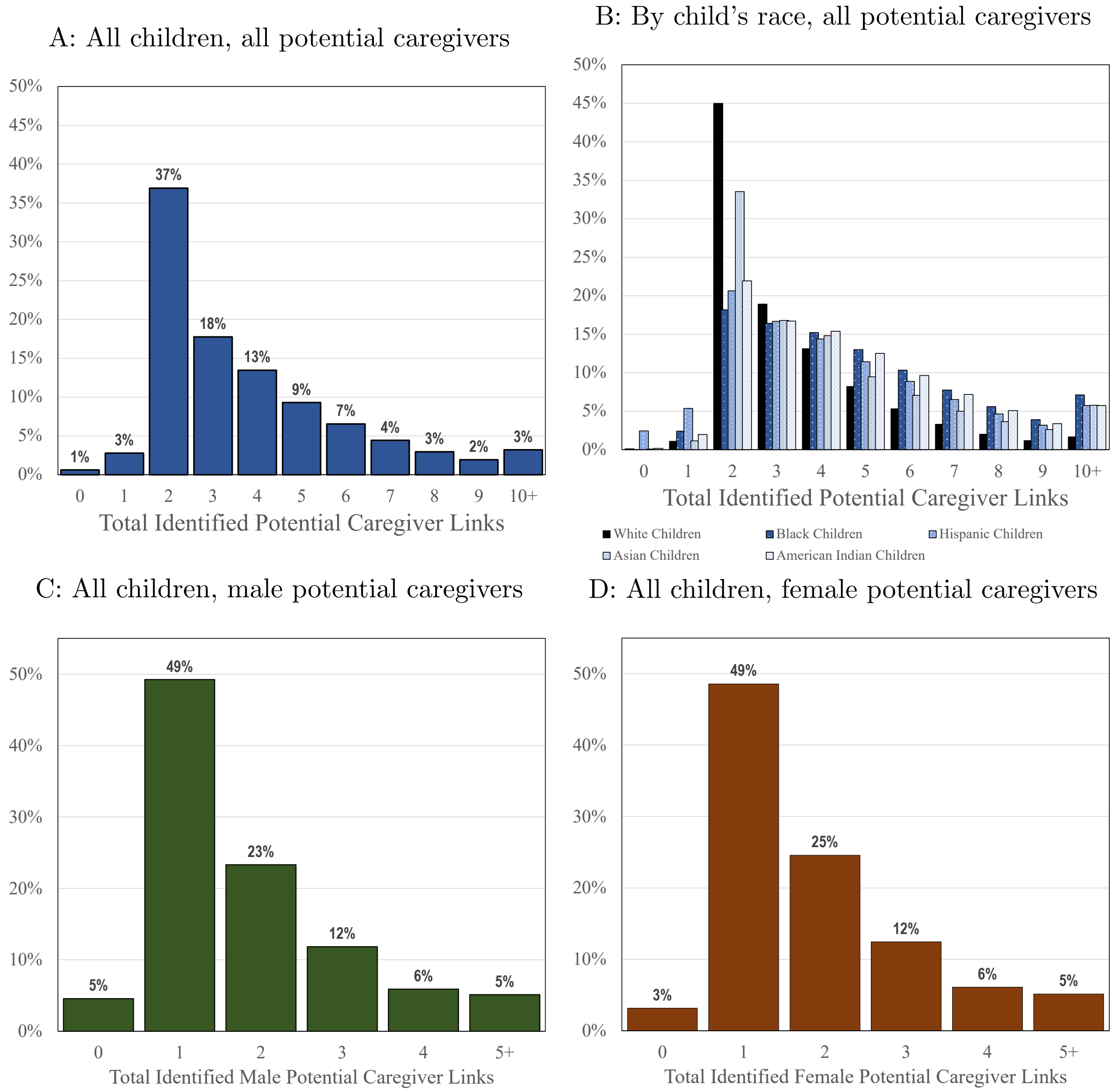
B: Number of children



Source: Calculations are based on the Census Numident, the Census BestRace files, and the CJARS relationship crosswalk.

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of females in the 1981 birth cohort in all states, as measured by the Census Numident. Race is measured using the Census BestRace files. Individuals are linked to the CJARS family crosswalk to measure fertility and age of first birth, defined as identifying a biological child and determining age at birth based on the year of birth of the child. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-009. These estimates can be compared to national public statistics on fertility. For Panel A, 2016 National Center for Health Statistics for age at first birth in 2000: overall 24.9, White 25.9, Black 22.3, Hispanic-Mexican 22.2 and Central/South American 24.8, Asian 27.8, and American Indian/Alaska Native 21.6 (Mathews and Hamilton, 2016). For Panel B, National Vital Statistics 2017 report birth rates: overall 1.766, White 1.666, Black 1.825, and Hispanic 2.01 (Mathews and Hamilton, 2019).

Figure A3: Distribution of total potential caregiver links identified per child

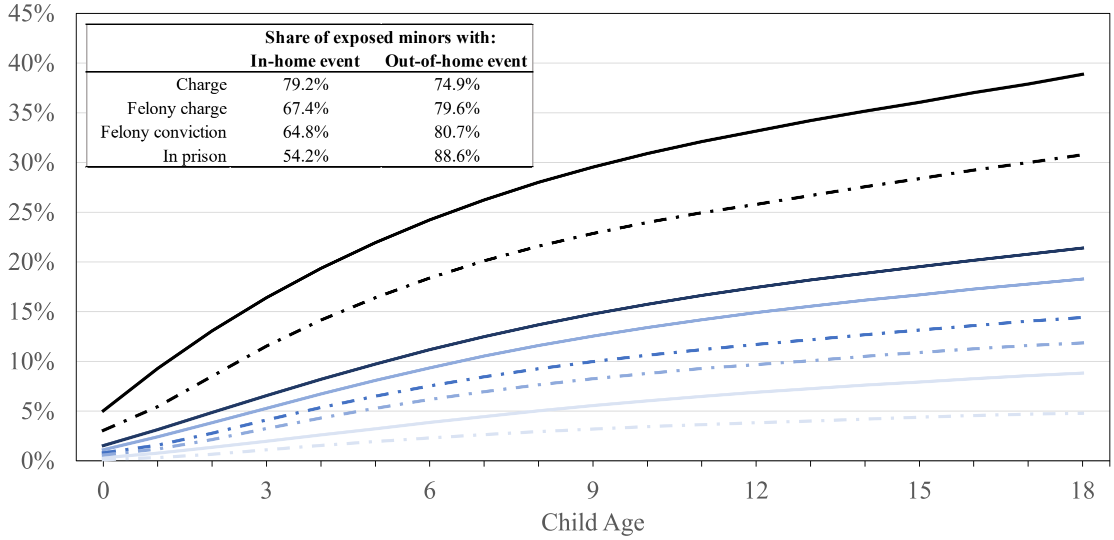


Source: Calculations are based on the Census Numident, the Census BestRace files, and the CJARS relationship crosswalk.

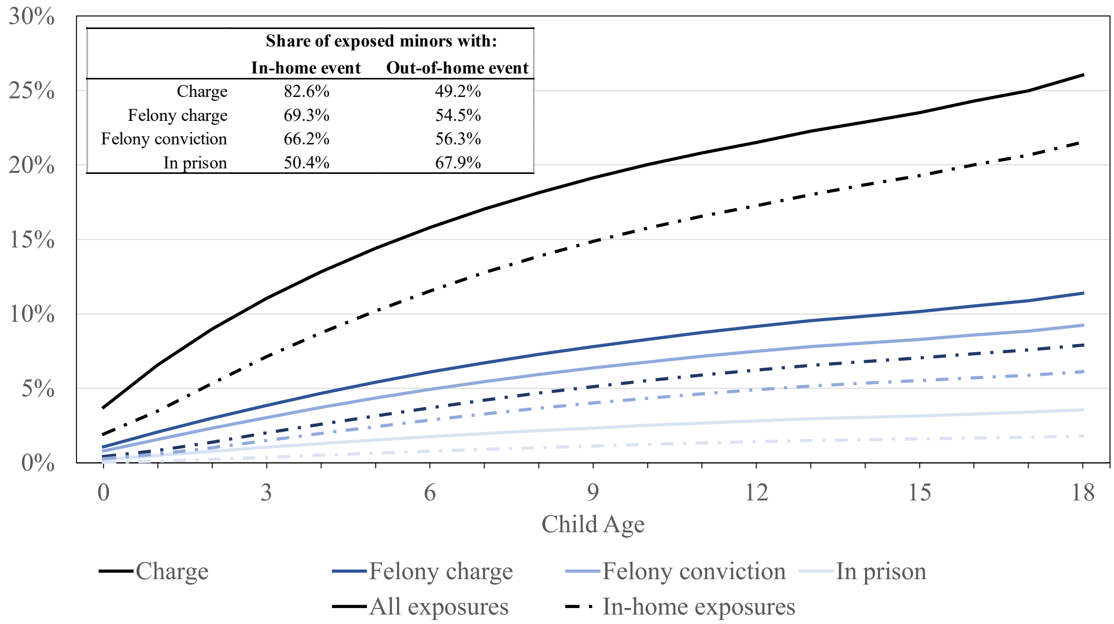
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in all states. Child's race is measured using the Census BestRace files. Potential caregivers are defined as biological parents, stepparents, adopted parents, foster parents, unclassified caregivers, grandparents, aunts/uncles, non-familial adult (cohabiting 2+ years), and unclassified adult (cohabiting 2+ years). All results were approved for release by the U.S. Census Bureau, authorization numbers CBDRB-FY22-ERD002-001 and CBDRB-FY22-ERD002-003.

Figure A4: Cumulative current or recent coresidency exposure to the criminal justice system

A: All potential caregivers



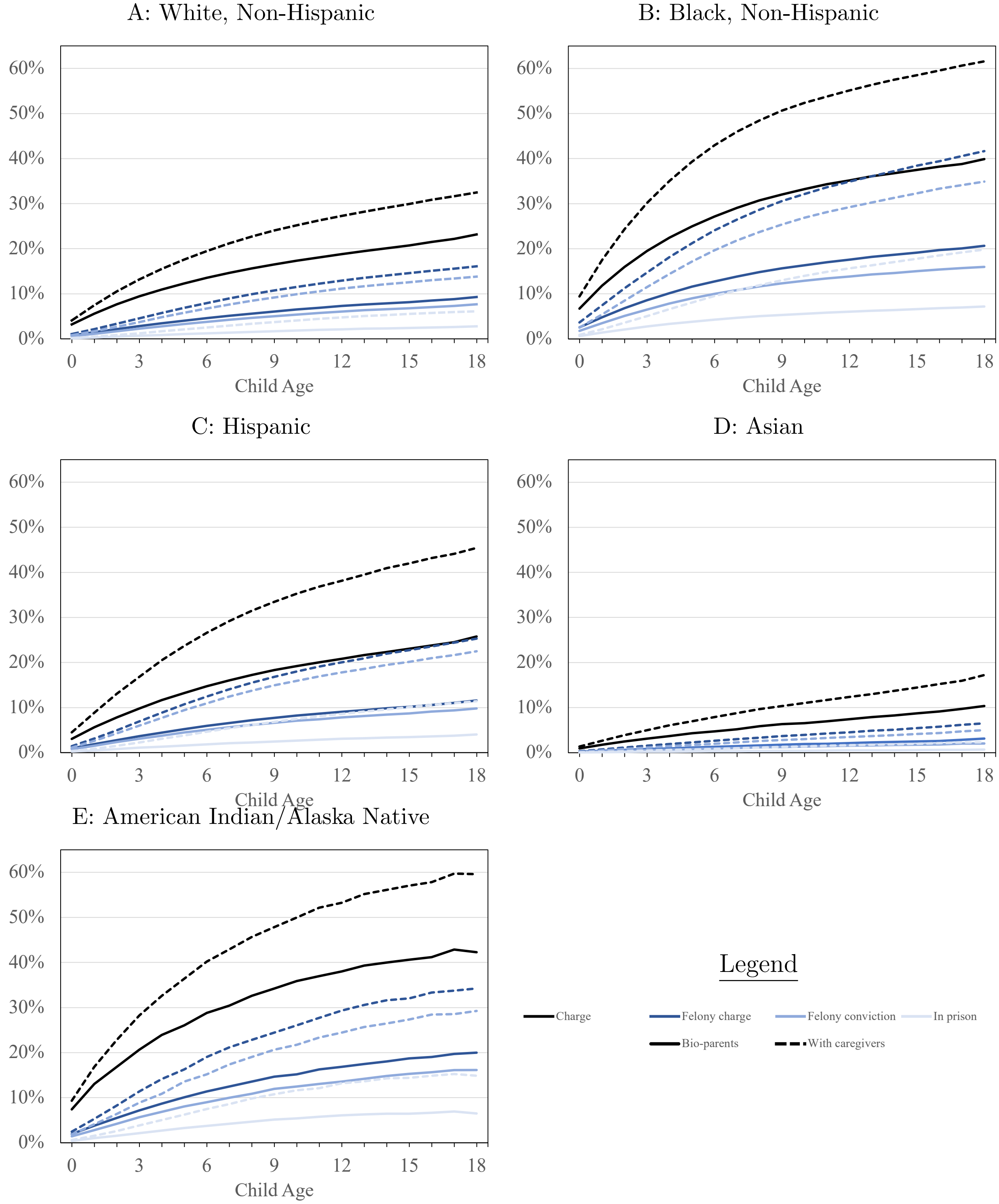
B: All biological parents



Source: Calculations are based on the Census Numident, CJARS, and CJARS residence and relations crosswalk.

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. In-home exposure is defined as exposure by an individual that was coresiding with the child in the year of the event or in the preceding two years. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval numbers CBDRB-FY22-ERD002-001 and CBDRB-FY22-ERD002-003.

Figure A5: Cumulative exposure to the criminal justice system, by child's race

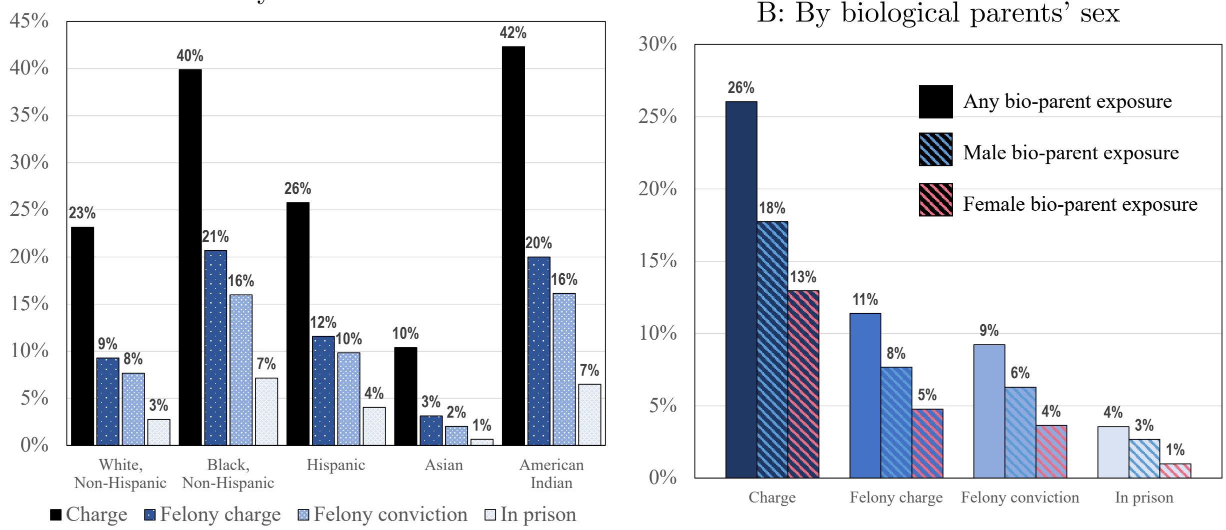


Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-001.

Figure A6: Heterogeneous cumulative exposure by biological parents

A: By child's race



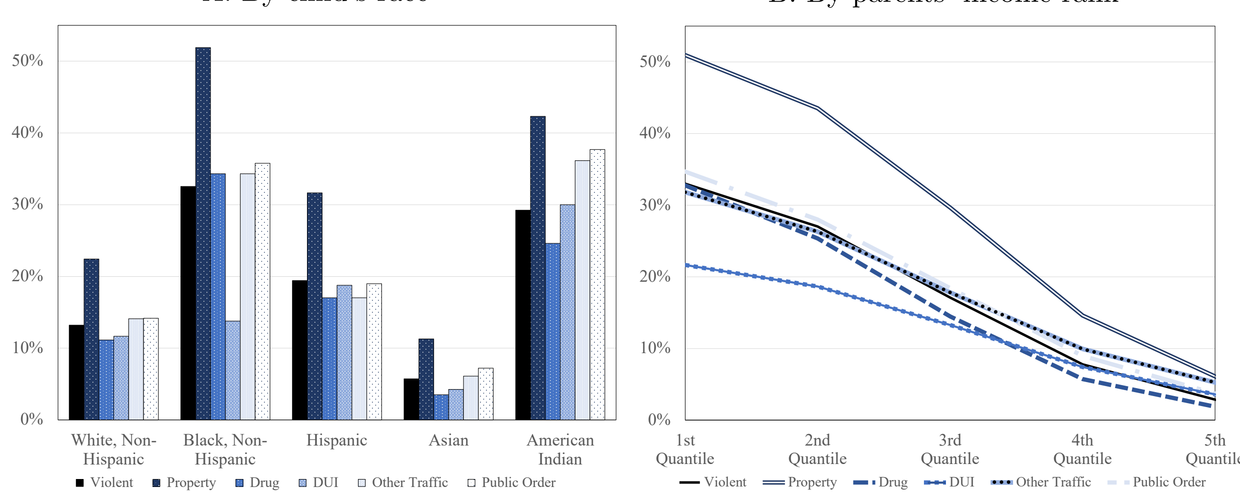
Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-001.

Figure A7: Heterogeneous cumulative exposure to criminal charges by offense type

A: By child's race

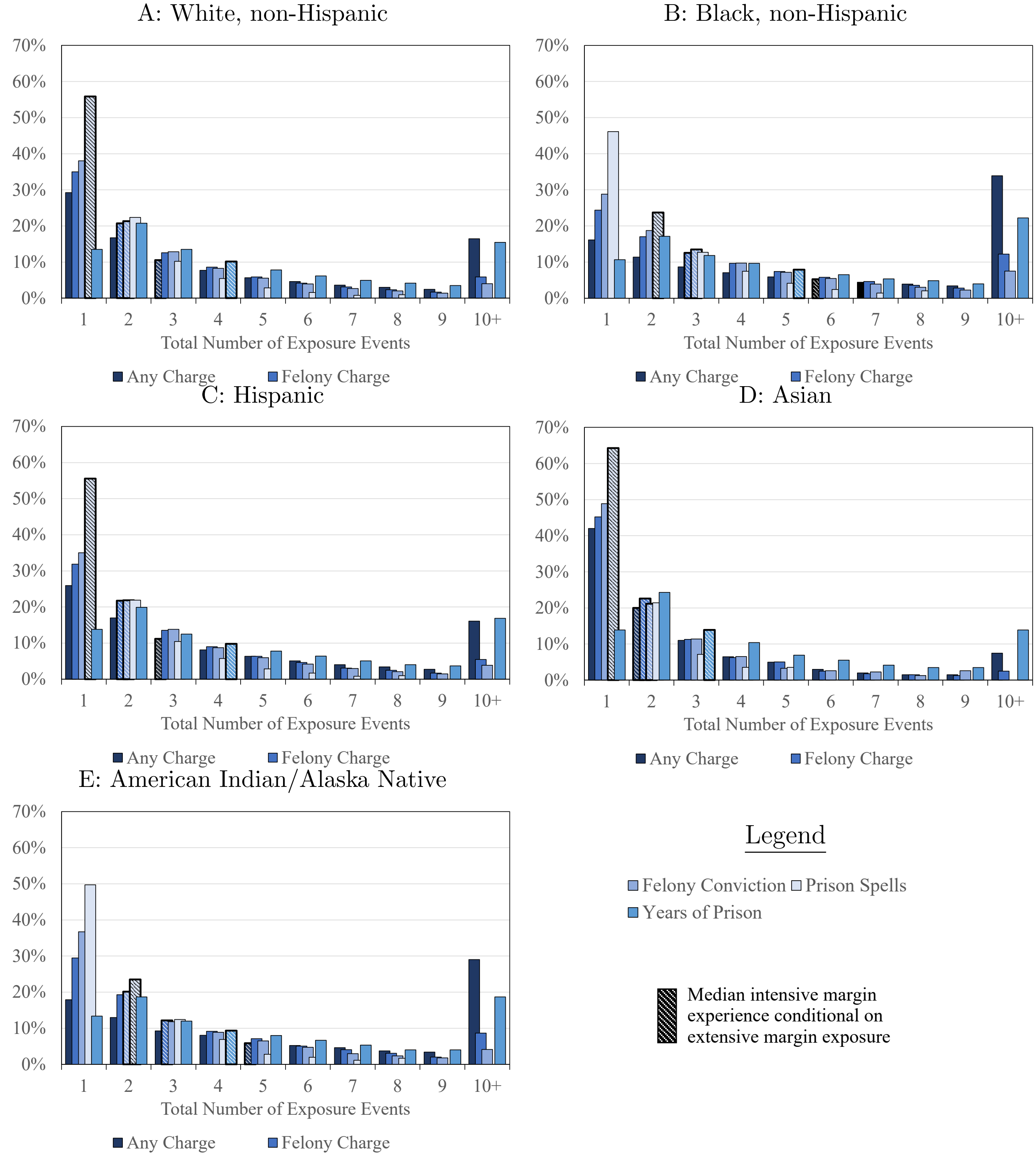
B: By parents' income rank



Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, the CJARS relations and residency crosswalks, and IRS Form 1040s (1999–2009 tax years).

Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies from birth until age 18. Average exposure by age 18 to specific charge types is depicted for children overall (Panel A), across race (Panel B), and across household income quantiles (Panel C). Income quantiles are determined using the average adjusted gross income reported on IRS Form 1040s, in which the child is claimed for the first five years. Children claimed on a form with negative AGI or never claimed in the first five years are not included in the sample. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-009.

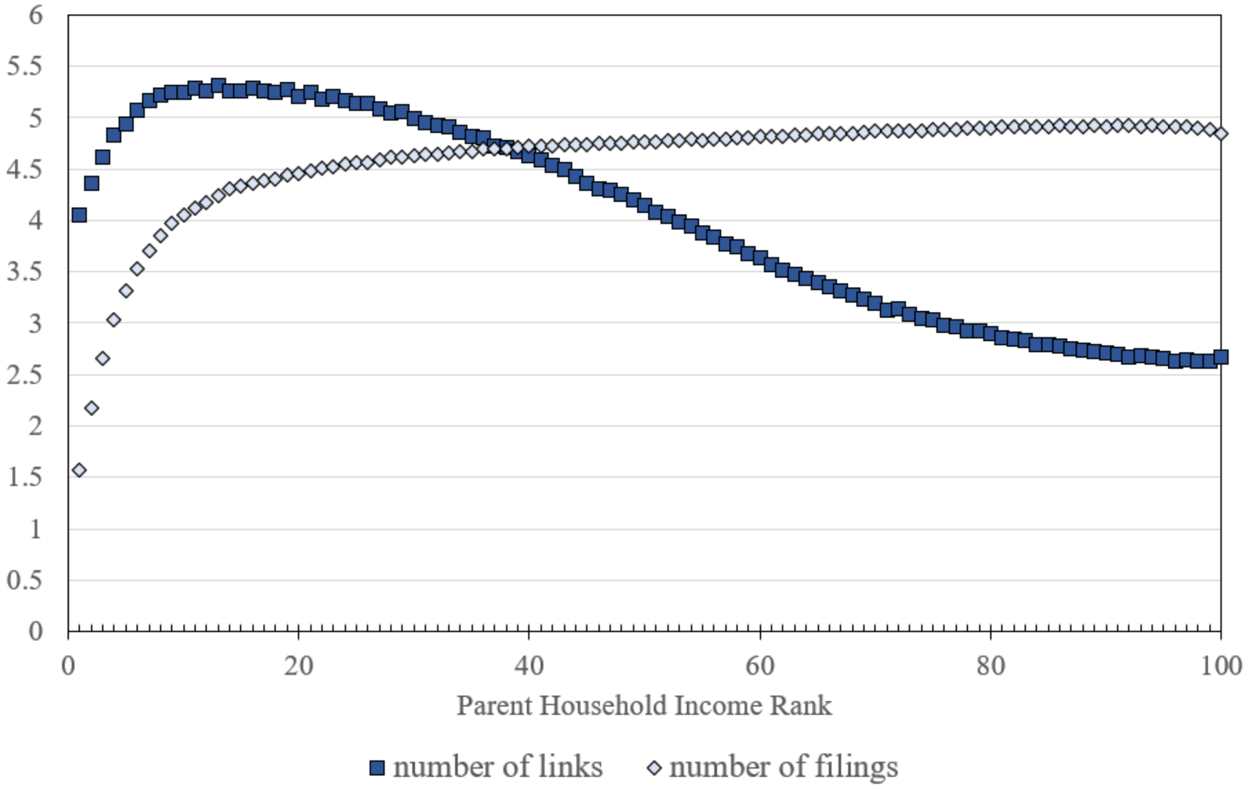
Figure A8: Intensive margin of criminal justice exposure by parents and other potential caregivers by age 18, by child's race



Source: Calculations are based on the Census Numident, the Census BestRace files, the CJARS relationship crosswalk, and CJARS.

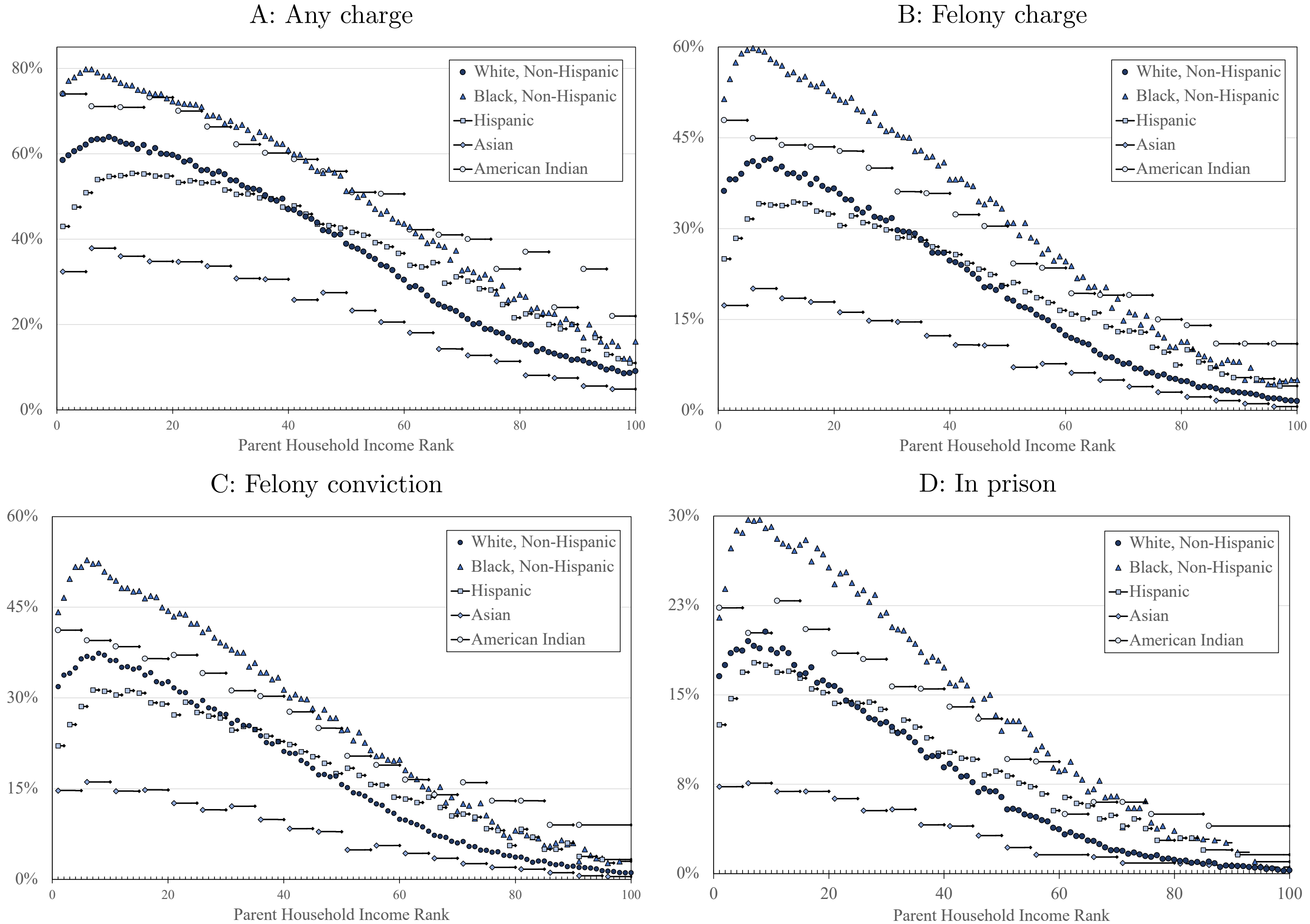
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies from birth until age 18. Distinct events are counted among children with any exposure. Thus, multiple charges filed on the same date are considered one event and similarly for the other types of criminal justice events. The number of events are truncated at 10+ events for all events *except* prison spells, which are top coded at 8+. Asian felony convictions and prison spells are top coded at 9+ and 5+ to preserve confidentiality, respectively. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval numbers CBDRB-FY22-ERD002-003 and CBDRB-FY22-ERD002-009.

Figure A9: Average number of caregiver links and tax filings by percentile rank



Source: Calculations are based on the Census Numident, the Census BestRace files, the CJARS relationship crosswalk, CJARS, and IRS Form 1040s.
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident born in 1999 and 2000 in CJARS-covered geographies from birth until age 18. Income percentile bins are determined using the average adjusted gross income reported on IRS Form 1040s, in which the child is claimed for the first five years. Children claimed on a form with negative AGI or never claimed in the first five years are not included in the sample. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-013.

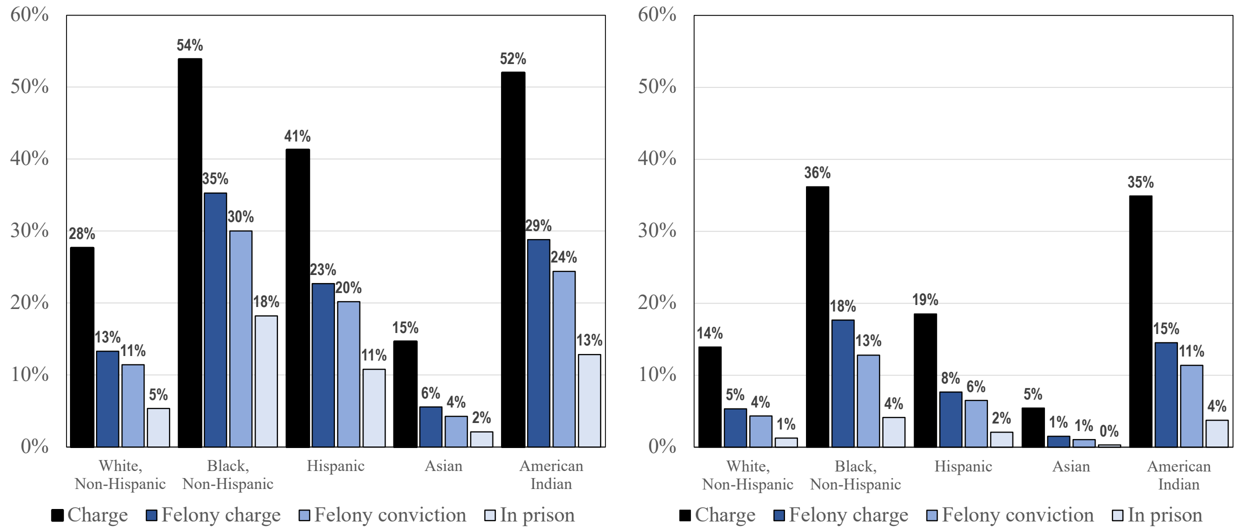
Figure A10: Exposure heterogeneity by parent income rank, by child's race



Source: Calculations are based on the Census Numident, the Census BestRace files, the CJARS relationship crosswalk, CJARS, and IRS Form 1040s.
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident born in 1999 and 2000 in CJARS-covered geographies from birth until age 18. Average exposure by age 18 is depicted for children across income percentile bins. Some bins, marked with horizontal black lines, are wider to satisfy disclosure requirements. Income percentile bins are determined using the average adjusted gross income reported on IRS Form 1040s, in which the child is claimed for the first five years. Children claimed on a form with negative AGI or never claimed in the first five years are not included in the sample. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-003.

Figure A11: Heterogeneous cumulative exposure by child race and adult sex

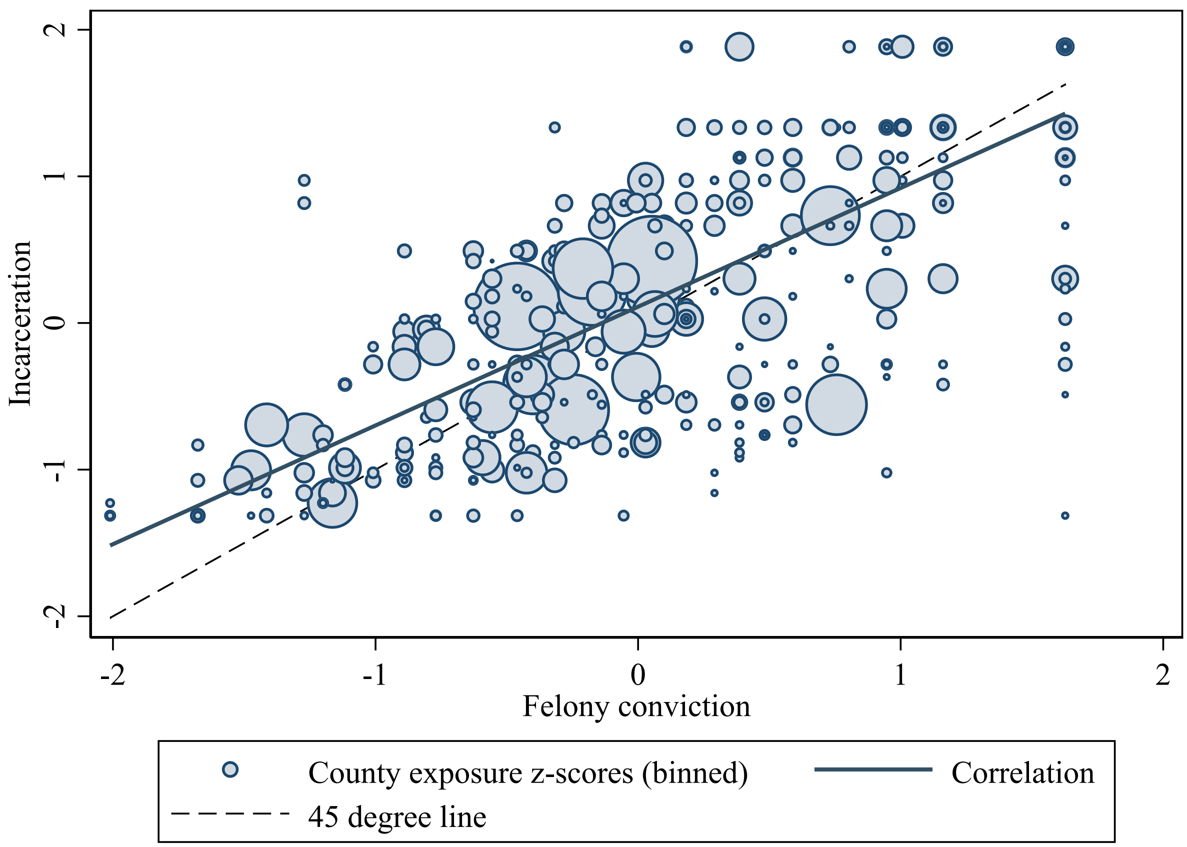
A: Male potential caregivers B: Female potential caregivers



Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

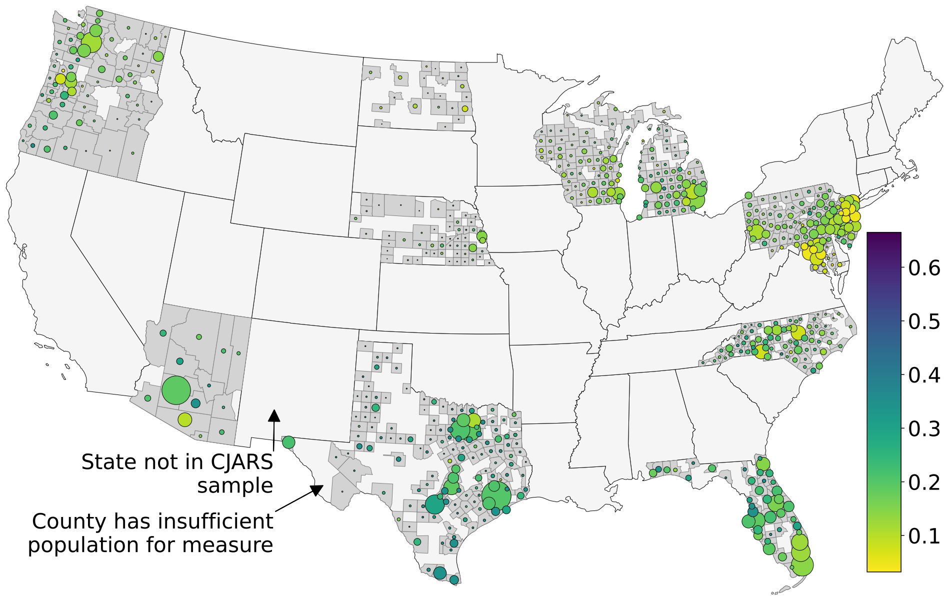
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY22-ERD002-001.

Figure A12: Relationship between felony conviction and incarceration exposure z-scores

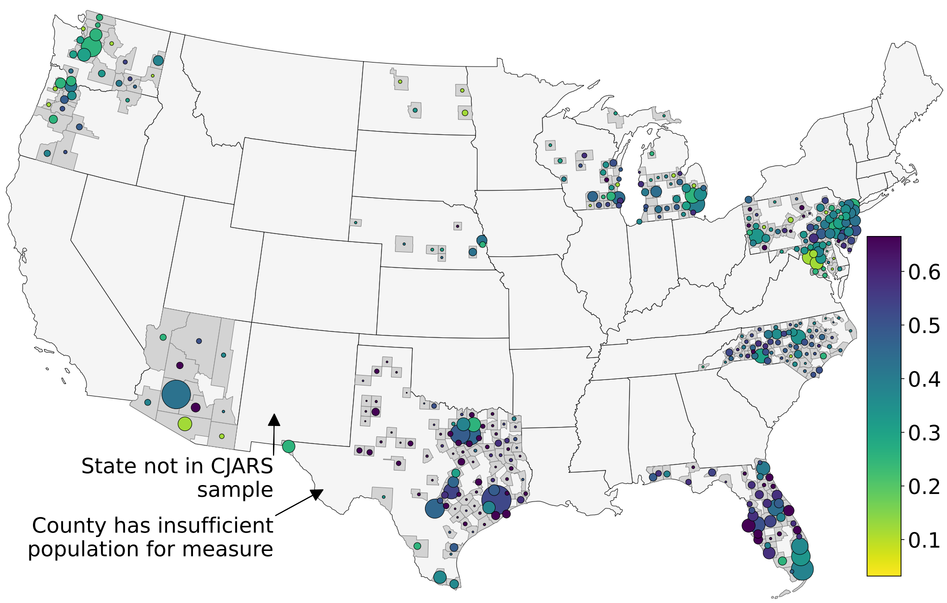


Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.
Notes: Estimates have been binned and rounded to preserve confidentiality, and scatter plots resized according to public county population sizes. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS dual-covered geographies (courts and prison coverage) from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year 2018. A regression of incarceration z-scoorese from disclosed exposure rates by county on felony conviction z-scores shows a correlation of 0.81 and R^2 of 0.58 for the subset of counties which include both court and incarceration coverage. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-013.

Figure A13: County variation in degree of child indirect exposure rates, by race
A: Map of county-level index variation among White children



B: Map of county-level index variation among Black children



Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, the CJARS relations and residency crosswalks, and IRS Form 1040s (1999–2009 tax years). Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies. Map markers are sized according to 2021 Census Bureau county total population estimates. All results were approved for release by the U.S. Census Bureau, Data Management System number P-7500378 and approval number CBDRB-FY23-0138.

Table A1: Correlation between estimated race-specific county-level exposure index and county and commuting zone characteristics

	Estimated Coefficient	P-Value
School Expenditure per Student	-0.429***	0.000
Opportunity Insights' Place Effect for Children with Parents in the 25th percentile of Income county-level	-0.260***	0.000
Teacher Student Ratio	-0.226***	0.000
Manufacturing Employment Share	-0.147***	0.000
Growth in Chinese Imports 1990-2000	-0.093**	0.017
Racial Segregation	-0.067*	0.085
Fraction with Commute less than 15 Minutes	-0.065*	0.094
Indicator for Urban Areas	-0.032	0.407
Income Segregation	0.026	0.510
Fraction Foreign Born	0.090**	0.021
Local Tax Rate	0.091**	0.019
Migration Inflow Rate	0.222***	0.000
Migration Outlflow Rate	0.232***	0.000
Fraction Black in the Population	0.245***	0.000
Number of CJARS-covered counties X race	2,900	

Notes: Reported are correlation coefficients (after standardizing variables to mean zero and standard deviation of 1) and corresponding p-values between county and commuting zone measures in CJARS-covered geographies. The exposure index is created using CJARS and all other measures are from Opportunity Insights publicly available data. The OI county effects are the percentage gain (or loss) in income at age 26 from spending one more year of childhood in a given county relative to the national mean. The CZ-level measures come from Chetty et al. (2014). * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

B Data appendix

Constructing the residency and relations crosswalks

The crosswalks are currently created for all individuals in the Census Numident with a valid birth year and born between 1960 and 2018.[34] The Census Numident is the "backbone" of the residence crosswalks, setting the population and identifying date and place of birth.[35] Address-level information is then harmonized for all subsequent years based on the 2000 and 2010 Decennial Censuses, American Community Survey (2001–2018), IRS Form 1040 tax filings (1969, 1974, 1979, 1984, 1989, 1994, 1995, 1998–2018 tax years), IRS Form 1040 electronic tax filings (2005, 2008–2012), Department of Housing and Urban Development (HUD) program data (Longitudinal PIC/TRACS: 1995–2016, 2018; PIC: 2000–2014; TRACS: 2000–2014) and county-level information from Medicare (2000–2017 EBD) and Medicaid (2000–2014 MSIS) enrollment databases, Indian Health Service (IHS) from 1999–2017, and the MAF-ARF (2000–2018).[36] Data are linked at the person-level using a Protected Identification Key (PIK) created through the Census Bureau's Person Identification Validation System (PVS).[37] Similarly, addresses are assigned MAFIDs, a numeric key, to protect PII. If more than one MAFID (i.e., address) is provided for an individual in a given year, the following ranking is applied: decennial census, IRS Form 1040, IRS Form 1040 ELF, American Community Survey, CMS EDB, HUD Longitudinal PIC/TRACS, HUD PIC, HUD TRACS, IHS, MAF-ARF, CMS MSIS.

The residence crosswalks are the basis of the familial crosswalks. First, for each year, all coresidence pairs are created at a given address. Group quarters and addresses with more than 20 individuals identified at the locations in a given year are suspect of not having familiar relations and thus not used to create pairwise relations among all cohabitants. This should not impact individuals living in apartment buildings, since individual units are

[34]The Census Numident is sourced from the Social Security Administration (SSA) Numident file, which tracks all events related to Social Security Numbers (SSN) and Individual Taxpayer Identification Numbers (ITINs) including applications, changes, and deaths. The Census Numident is a research file that de-identifies the information by assigning a unique Protected Identification Key (PIK) for all SSNs and ITINs. For further explanation of these files, see Genadek et al. (2022).

[35]We use a place of birth crosswalk which links unique place names and states to county and state FIPS codes.

[36]We note that the MAF-ARF is used as a last resort when determining the best address for each individual in each year; this is because multiple address are reported per individual in years prior to 2012 with only one address reported after 2012, without knowing the source of the multiple addresses or the single address chosen post 2012.

[37]PIKs are used to link data at the person level within the Census Bureau's Data Linkage Infrastructure. PIKs can be assigned deterministically using only SSN or probabilistically using names, dates of birth, addresses, and other information as inputs into the Person Identification Validation System (PVS). For further explanation of this process, see Wagner and Lane (2014).

assigned unique address identification numbers. Instead, examples of group quarters include dormitory facilities, assisted living facilities, homeless shelters, nursing homes, and prisons. For children who are living temporarily in group quarters (like a homeless or emergency shelter), we rely on the years of their childhood when they are not living in group quarters environments to build their relationship information. So, if they coreside with their parents and other potential caregivers before or after the period of time in group quarters, there will be no loss of linkages based on our processing algorithm.

Relationships are enhanced above cohabitation based on information in the 2000 and 2010 decennial censuses, American Community Survey (2001–2018), IRS Form 1040 tax filings (1969, 1974, 1979, 1984, 1989, 1994, 1995, 1998–2018 tax years), IRS Form 1040 electronic tax filings (2005, 2008–2012), and HUD program data (1995–2018, 2018). The Decennial Censuses, American Community Surveys, and HUD program data each provide relationships between the household head and other household members, which is used to directly establish relationship types and infer the relationship between household members. Additionally, tax filing and claiming behavior establish spousal relationships and dependents. Finally, we include the Census Household Composition Key (CHCK) which creates links between children and parents based on information on birth certificates for children born between 1999–2018 (Luque and Wagner, 2015).[38] Children that do not have parental links established by the CHCK file could be due to the father's or mother's information being left off of the birth certificate, inaccurate parent information, the parent not being assigned a PIK (SSN or ITIN), or an inability to match the child-parent pair to the same address to confirm the link (Luque and Wagner, 2015; Genadek et al., 2022; Bond et al., 2014). We provided new statistics validating the relationship pairs identified by the CHCK file. First, We confirm that 93% of the biological relationships identified by our crosswalk are also observed in the CHCK file. Second, we document that 70% of all CHCK relations are confirmed as biological parents by survey microdata or HUD program data, which increases to 97% once unclassified caregivers (those observed claiming a child on a 1040 tax form accompanied by no other observable information) are reclassified as biological parents.

Relationship types are established by combining the multitude of observations between pairs across data sources and years into the following set:Are any of the 13 year cut offs geq or leq?

Many relations can only be classified into the main category without the additional detailed information required to classify the relationship pair among the subcategories, for several

[38]The Census Bureau uses parents' names from birth certificates to probabilistically assign PIKs through the PVS and the child's SSN which uniquely determines the PIK to match to children in the Census Numident ages 0–18 as of 2018 and 2019. Since parents' SSNs are not available, the CHCK file requires that the child-parent link be confirmed at the same address in the PVS reference file.

Table B1: Relationship types in CJARS crosswalks

Relation Code	Relation Description
10	Cohabiting adults (=¡13 years apart)
11	Spouse
12	Domestic partner
13	Romantic unmarried (e.g., boyfriend/girlfriend)
14	Unclassified romantic
15	Adult, non-romantic (e.g., roommate/boarder)
20	Cohabiting adult-minor (¿13 years apart)
21	Bio parent - child
22	Adopted parent - child
23	Stepparent - child
24	Foster parent - child
25	Unclassified parent - child
26	Parent - child-in-law
27	Grandparent-grandchild
28	Aunt/uncle-niece/nephew
29	Non-familial adult - child
40	Cohabiting minors (=¡13 years apart)
41	Bio-siblings
42	Adopted-siblings
43	Step-siblings
44	Foster-siblings
45	Unclassified siblings
45	Cousins
45	Second cousins
45	Siblings-in-law

reasons. First, relationships in the decennial censuses, American Community Survey, and HUD program data are all expressed in relation to the household head. Several assumptions are imposed to infer relations between other household members, but often there is not enough information to classify a link beyond an unclassified parent-child link.[39] Second, the American Community Survey between 2001–2007 and 2010 Decennial Census uses broader relationship definitions.[40] Finally, parental relations that are established only in the tax

[39]Some of the assumptions imposed to define parent-child relations (and vice versa): 1). if a household head has a biological child, then the spouse to the household head is also linked as a biological parent, 2). if a household head has a stepchild, then the spouse to the household head is assumed to be the biological parent, 3). if a household head has an adopted child, then the spouse to the household head is assumed to be an adopted parent, and 4). if a household head has a foster child, then the spouse to the household head is assumed to be the foster parent as well. Examples of inferred parent-child links where subclassification can not be ascertained: 1). a household head linked to their parent is not further classified as biological, step, adopted, or foster 2). a spouse of a household head linked to the household head's mother/father-in-law is not further classified as biological, step, adopted or foster 3). a sibling of the household head linked to the niece/nephew of a household head, subject to age restrictions and other information if available 4). a child of a household head linked to a grandchild of the household head, subject to age restrictions and other information if available.

[40]The following relationship types to the household head were removed from the 2010 Decennial Census:

records and not observed in the Census surveys or HUD program data (or are observed with ambiguous relationships) can only be classified as a parent with no further information to sub-classify into biological, step, adopted, foster, aunt/uncle, etc.[41]

A relation pair may be observed multiple times across source files and years. Relationship types only need to be defined once in order to assign it to the cohabiting pair. This approach is beneficial since individuals may be observed multiple years in the tax records, but without detailed relational information and may be observed only once by the Decennial Census or ACS.

Relationship types between pairs are sequentially established based on the strength of the source information. For example, relations established in Census with the head of household directly define a relationship, while relations between other household members are inferred. Figure B1 demonstrates the iterative process and assumptions used when defining relationship types.

Performance of residential and relationship crosswalks

First, we benchmark our fertility statistics, as measured in the CJARS family crosswalk, to published statistics in the 2016 National Center for Health Statistics and 2017 National Vital Statistics System reports (Mathews and Hamilton, 2016, 2019). In Figure A2 Panel A, we show the cumulative distribution of age at first birth by race for females born in the U.S. in 1981, as measured by the Census Numident.[42] The average age of first birth overall is 25.01 based on our crosswalks, which is inline with an overall age of first birth in 2000 and 2014 of 24.9 and 26.3, respectively (Mathews and Hamilton, 2016). Asian women have the highest average age at first birth (our estimate 28.15; NCHS in 2000: 27.8), followed by White (25.67; 25.9), Hispanic (23.23; Mexican 22.2, Central and South American 24.8), American Indian/Alaska Native (22.85; 21.6), and Black (22.67; 22.3) women. In Panel B, we show the number of births observed until the age of 37, the latest possible age for this cohort. Again, our observed birth rates for women born in 1981 overall (1.673) are inline with

sibling-in-law, nephew/niece, uncle/aunt, cousin, grandparent, and foster child. The ACS did not offer more detailed classifications for parent-child links (namely, biological, adopted, or step) or in-law links (parent or child) until 2008.

[41] A parent-child relationship is assumed if the age difference between the individuals is less than 45 years and a grandparent-child relation if the age gap is 45 years or greater. However, it is possible for an aunt or uncle to claim a child on tax records, although treating them as an unclassified parent in this circumstance is likely permissible for our application.

[42] Due to data availability, we do not observe fertility beyond age 37 for this cohort and have more limited ability to observe birth prior to age 18 since the CHCK file covers children starting in 1999. Observed births are measured in our crosswalks as a reported biological child and age at birth is defined using the year of birth for the child.

the reported birth rate by NVSS in (1.766). American Indian/Alaska Native women have the highest number of observed births (our estimate: 2.047, NVSS not available), followed by Hispanic (1.823; 2.01), Black (1.744; 1.825), White (1.655; 1.666), and Asian (1.39; not available) women.

Next, we turn to our ability to measure caregiver links for children in our core sample. Using the previously described crosswalks, we identify female (male) biological parents for 90% (76%) of children born between 1999 and 2005 (Figure IA). When we relax the requirement for an explicitly defined relationship status and expand to include other types of adult household members, we observe 97% and 95% of children are linked with one or more female and male adult potential caregivers, respectively.[43]

There are important differences by race, due to both systematic differences in household structure and in our ability to observe potential caregivers in administrative and survey records. First, we see that only 55% of Black, non-Hispanic children are connected to a biological male parent in the data. This could be due to either fathers being excluded from birth records, not coresiding with children during household surveys, or not claiming their children as dependents in tax filings. However, White, non-Hispanic and Black, non-Hispanic children have very similar rates of being linked to a female biological parent (∼94%). Second, Hispanic children are much less likely to be observed with a female biological parent (75%) as well as male biological parents (60%), and just less than 90% are observed with a male and female potential caregiver; this is likely the result of these individuals being less likely to have a Social Security Number (SSN) or Individual Tax Identification Number (ITIN), which is needed for individuals to receive a PIK and be linked across data sets within the Census Bureau's Data Linkage Infrastructure (Bond et al., 2014).

Figure IB documents the share of children born between 1999 and 2005 observed with other types of intergenerational relationships in the household. We find that 4.7%, 22%, 29%, and 46.2% of children are observed with a step/adopted/foster parent, extended family (grandparent/aunt/uncle), unclassified caregivers, and unclassified cohabiting adults, respectively.[44] Unclassified caregivers, which occur when we observe an adult-child link resulting of

[43] Figure A3 documents the distribution of number of links identified overall (Panel A) and by racial and ethnic subgroup (Panel B).

[44] Fewer children are observed with step/adopted/foster parents than what is observed in the SIPP (Sweeney, 2010; Kreider and Ellis, 2011; Raley and Sweeney, 2020); this is likely due to relationship misclassification into biological parents and unclassified caregivers due to relations being reported to the household head in the Census surveys and HUD program data and a lack of relational information beyond claiming behavior on tax forms. For example, if a household head has a biological child, then it is assumed they share the biological child with their spouse. However, the relation could be a step or adopted parent. Similarly, if a child is claimed by someone with an age gap less than 45 years and the relation is not observed in the CHCK file, then the relation is considered an unclassified caregiver. However, the relation could be a step/adopted/foster parent, an aunt or uncle, or a younger grandparent.

dependency claims in IRS tax records without any other information to pin down the nature of their relationship, are more likely in multigenerational households, and among biological parents that are left off of birth records (as proxied by the CHCK file).[45] Importantly, all these relations *seem* like important parental figures given the tax filing relationship even if they are not included in the CHCK, which is our closest approximation to a birth record database. Unclassified adults, in contrast, are other cohabiting relations that are either explicitly classified as non-familial in Census Bureau surveys or just adults that we observe coresiding at the same address as the child (e.g., live-in boyfriends, roommates, etc); notably, we require that these relations must coreside for 2 years or more in order to focus on those with greater potential familial attachment.[46]

Again, there are important differences in the share of children that are observed with various caregiver relations by race. Minority children are much more likely to have an extended family caregiver (Black, non-Hispanic 38%, Hispanic 28%, Asian 32%, and American Indian/Alaska Native 31%) than their White, non-Hispanic counterparts (17%); this is consistent with previously documented differences in household structures by race and ethnicity in the U.S. (e.g., Lofquist, 2012; Cohen and Passel, 2018).

Approximately 48.6% (49.3%) of children are linked with just one female (male) potential caregiver, a grouping that combines biological parents and other potential adult caregivers in their household. 24.6% (23.3%) of children are observed with two female (male) potential caregivers, while 23.7% (22.8%) are linked with 3 or more female (male) potential caregivers. A variety of living circumstances could give rise to more than one potential caregiver of the same sex being linked with a child, for example: (1) parents with multiple romantic partners (due to divorce or separation) while raising their children, (2) households with same-sex romantic partners, (3) multigenerational households, or (4) doubled up households where multiple families share the same accommodations. The high rate of children linked with 2 or more potential caregivers of the same sex reflects the experience of many children today in the U.S. of growing up with multiple adult influences in their households beyond the traditional nuclear family.

[45] Household surveys enumerate relationships of all individuals in the household with respect to the head of household. Relationships between other individuals must be inferred, which is increasingly complicated in households that extend beyond nuclear families.

[46] Utilizing a 2-year coresidency requirement also minimizes the influence of errors in the probabilistic record linking process for address information that might lead children to be labeled as coresiding with adults who in fact do not live at the same address.

Figure B1: Sequential process to establish relations beyond cohabitation

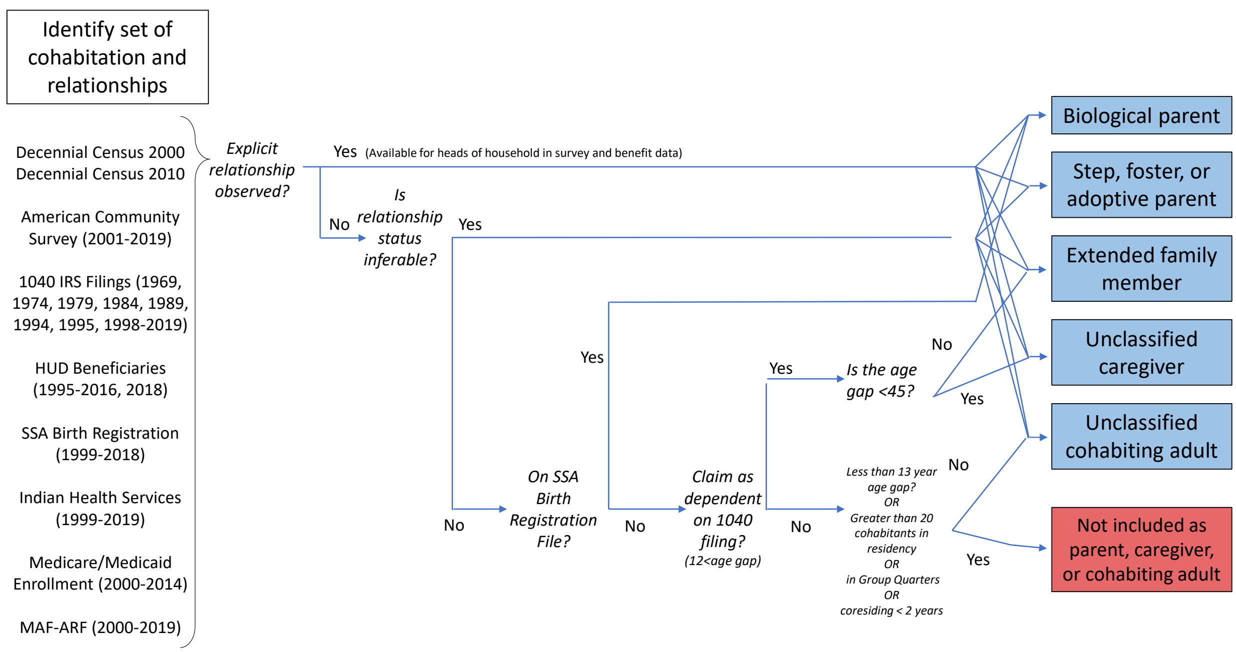


Table B2: Source files contributing to the residence crosswalk

Source	Years	Variables
MAF-X	2017	MAFID, state, county, group quarters flag
IRS Form 1040	1969	primary filer, MAFID, state
—	1974, 1979, 1984,1989	primary and secondary filer, MAFID, state
—	1994, 1995, 1998–2019	primary and secondary filer, four dependents, MAFID, state
IRS Form 1040 ELF	2005, 2008–2012	primary and secondary filer, 20 dependents
Decennial Census	2000, 2010	household members, MAFID, state, county, group quarters flag
ACS	2001–2004†	household members, state, county
—	2005–2018	household members, state, county, MAFID, group quarters flag
HUD Longitudinal PIC/TRACS	1995–2016, 2018	household members of enrollees, state, county, MAFID
HUD PIC	2000–2014	household members of enrollees, state, county, MAFID
HUD TRACS	2000–2014	household members of enrollees, state, county, MAFID
CMS EDB	2000–2019	enrollees, state, county, MAFID
CMS MSIS	2000–2014	enrollees, state, county
Indian Health Service	1999–2019	enrollees, state, county, MAFID
MAF-ARF	2000–2018	individuals with SSN or ITIN, state, county, MAFID
Census Numident	2021Q1	individuals with SSN or ITIN, place of birth (linked to state, county, and commuting zone), date of birth, date of death, sex, race

† There are small samples during the ACS trial years between 2001 and 2004, so while statistical information is not used for these years, respondents' address-level information and household relationships are used in the creation of these crosswalks.

Figure B2: Construction of residential and relations crosswalks

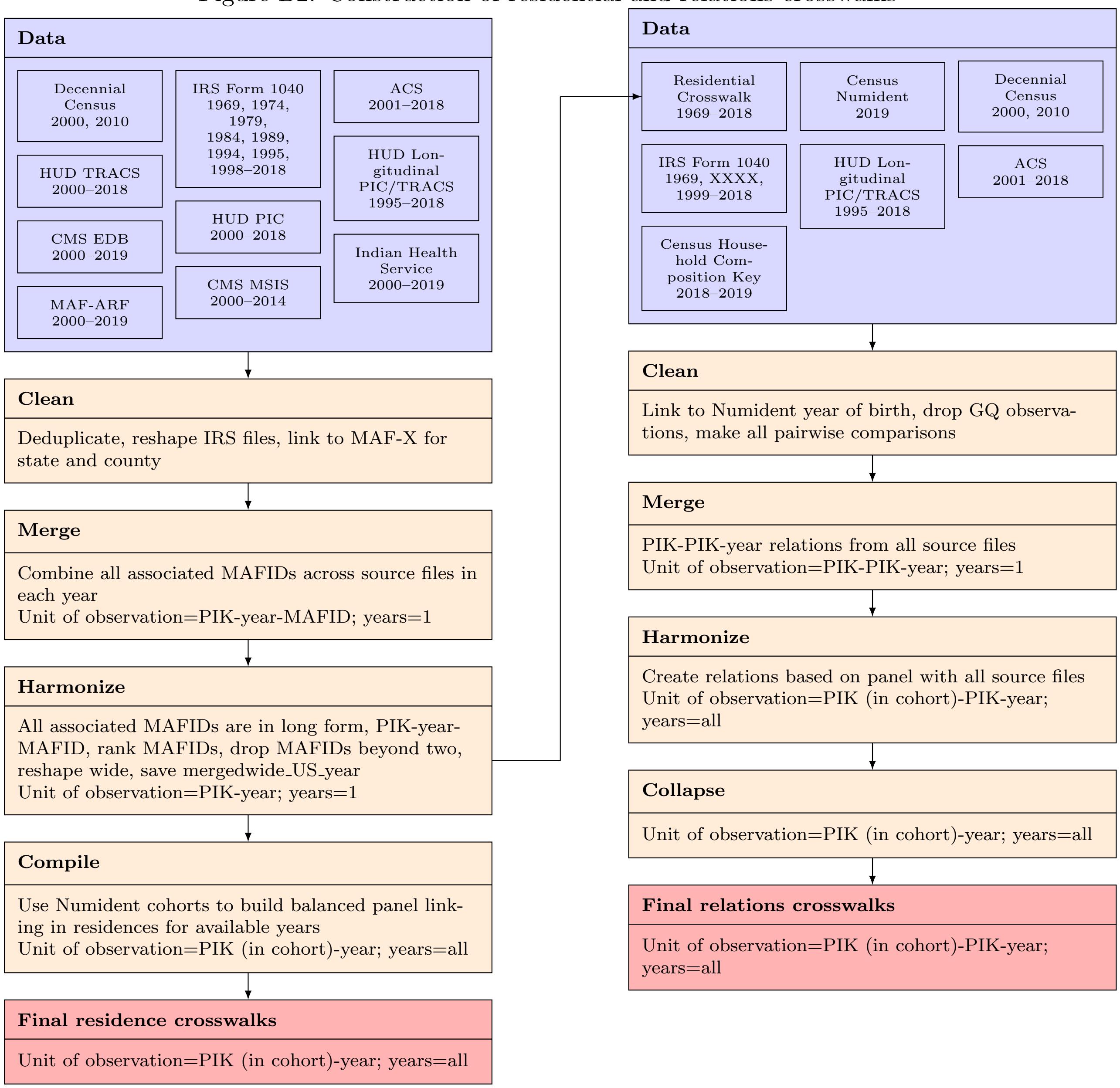
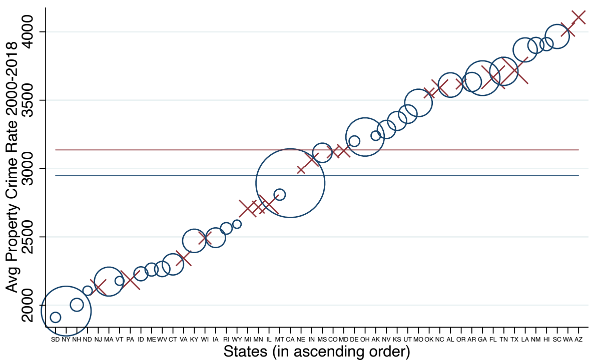
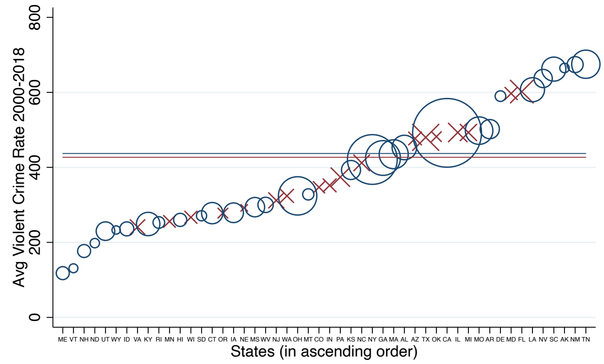


Figure B3: State comparisons, crime and criminal justice outcomes

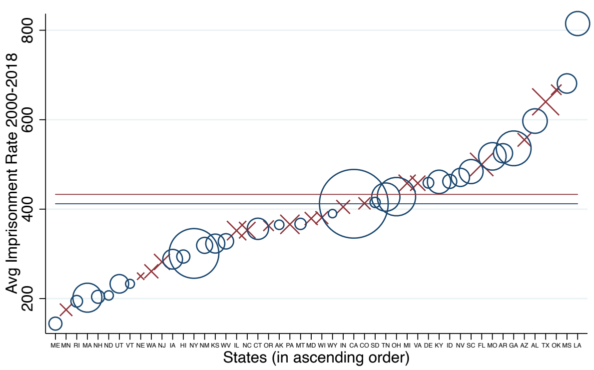
A: Property Crime Rates (UCR)

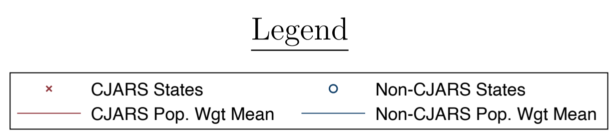


B: Violent Crime Rates (UCR)



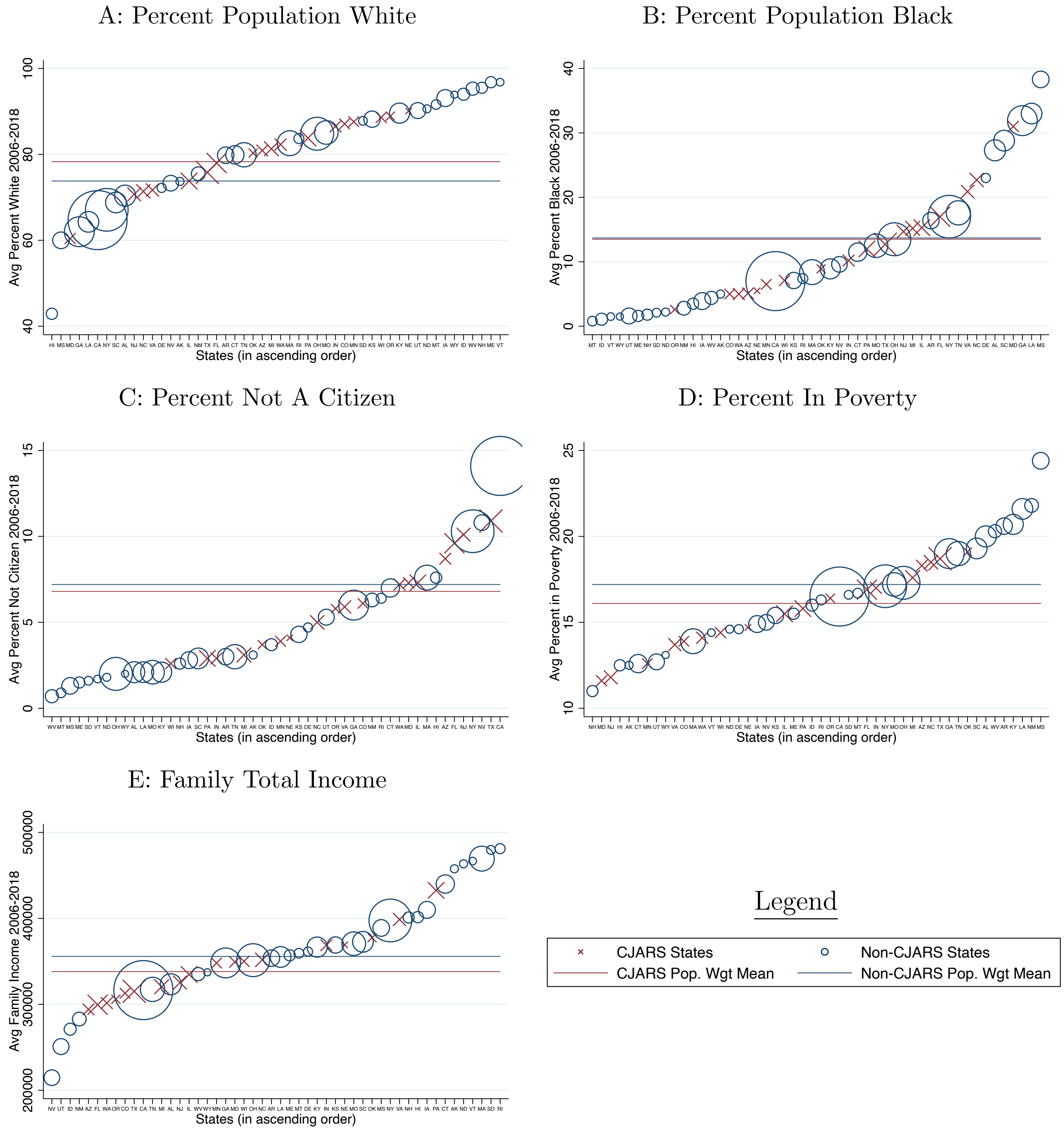
C: Incarceration Rates (BJS)





Notes: Data come from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program and the Bureau of Justice Statistics National Prisoner Statistics program. The rates per 100,000 residents have been averaged for each state over the period 2000–2018. Marker sizes are proportional to each state's population, averaged over the years 2000–2018.

Figure B4: State comparisons, socioeconomic outcomes



Notes: Data come from the IPUMS USA 2006–2018 ACS, with state averages reported and weighted by the average population during the same time period (Ruggles et al., 2021). Marker sizes are proportional to each state's population averaged over the years 2000–2018.

Table B3: Source files contributing to the relations crosswalk

Source	Years	Variables
Residential Crosswalk	1969–2019	cohabiting pairs, except those in group quarters or at address with more than 20 individuals in a single year
IRS Form 1040	1974, 1979, 1984, 1989	primary and secondary filer
—	1994, 1995, 1998–2019	primary and secondary filer, four dependents
IRS Form 1040 ELF	2005, 2008–2012	primary and secondary filer, 20 dependents
Decennial Census	2000, 2010	household members and relation to household head
ACS	2001–2018†	household members and relation to household head
HUD Longitudinal PIC/TRACS	1995–2016, 2018	household members of enrollees and relation to household head
Census Household Comp. Key	2018, 2019	individuals with SSN between 0 and 18 years of age, child, mother, father links
Census Numident	2021Q2	individuals with SSN or ITIN, place of birth (linked to state, county, and commuting zone), date of birth, date of death, sex, race

† There are small samples during the ACS trial years between 2001 and 2004, so while statistical information is not used for these years, respondents' address-level information and household relationships are used in the creation of these crosswalks.

Table B4: Ten most common criminal charges within each offense category

Violent	Property	Drug
1200 Aggravated assault	2040 Forgery/fraud	3150 Possession/use of marijuana
1240 Extortion threat	2070 Theft	3160 Possession/use of unspecified drug
1180 Armed robbery	2010 Burglary	3250 Drug paraphernalia
1230 Simple assault	2140 Criminal trespass	3080 Distribution, drug unspecified
1990 Other violent offense	2050 Grand theft	3110 Possession/use of cocaine or crack
1090 Child molestation	2110 Destruction of property	3990 Other drug offense
1220 Child abuse	2060 Petty theft	3140 Possession/use of controlled substance
1070 Rape	2100 Receiving stolen property	3070 Distribution of marijuana
1010 Murder	2120 Hit and run driving, property damage	3030 Distribution of cocaine or crack
1060 Kidnapping	2130 Unauthorized use of a vehicle	3100 Possession of amphetamines
Driving under the influence	Public order	Criminal traffic
4020 Driving under the influence of alcohol	5130 Obstruction/resisting arrest	6010 Traffic offense, minor
4010 Driving while intoxicated	5170 Disorderly conduct offense	
4030 Driving under the influence of drugs	5990 Public order offense, other	
	5180 Liquor law violation	
	5040 Weapons offense	
	5090 Other court offense	
	5080 Contempt of court/court order violation	
	5070 Probation violation	
	5150 Commercialized vice	
	5110 Offense against morals/decency	

Source: Estimates calculated from CJARS court records held by the University of Michigan and not protected by 13 USC §9a.
Notes: Offense codes follow the classification schema outlined in Choi et al. (2023).