Measuring Intergenerational Exposure to the U.S. Justice System: Evidence from Longitudinal Links between Survey and Administrative Data

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Abstract

Intergenerational exposure to the justice system is both a marker of vulnerability among children and a measurement of the potential unintended externalities of crime policy in the U.S. Estimating the size of this population has been hampered by inadequate data resources, including the inability to (1) observe non-incarceration sources of exposure, (2) follow children throughout their childhood, and (3) measure multiple adult influences in increasingly dynamic households. To overcome these challenges, we leverage billions of restricted administrative and survey records linked with the Criminal Justice Administrative Records System (CJARS). We find substantially larger prevalences of intergenerational exposure to the criminal justice system than previously reported: 9% of children born between 1999–2005 were intergenerationally exposed to prison, 18% to a felony conviction, and 39% to any criminal charge; charge exposure rates reach as high as 62% for Black children. We regress these newly quantified types of exposure on measures of child well-being to gauge their importance and find that all types of exposure (parent vs. non-parent, prison vs. charges, current vs. previous) are strongly negatively correlated with development outcomes, suggesting substantially more U.S. children are harmed by crime and criminal justice than previously thought.

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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, Devereux, and Salvanes 2007; Campbell et al. 2014), education (Deming 2009; Dynarski, Hyman, and Schanzenbach 2013), housing (Chetty, Hendren, and Katz 2016), and financial well-being (Hoynes, Schanzenbach, and Almond 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 aiming 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, Pecenco, and Weaver 2021; Arteaga 2018). 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 intergenerational exposure to the justice system comes with several challenging hurdles. Data limitations and a prior focus on incarceration have yielded almost exclusively intergenerational 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. Likewise, existing estimates typically quantify contemporaneous intergenerational exposure at a given point in time (e.g., Mumola 2000; Glaze and Maruschak 2008), which may be insufficient if intergenerational exposure events produce long-term scarring effects.[2] Finally,

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

[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 L. H. Andersen 2015) or use small longitudinal surveys like the newly fielded Family History of Incarceration

the literature predominately focuses on biological parents as the originating sources of intergenerational justice exposure, which overlooks a well established literature on changing household structure in the U.S.,[3] especially among racial and ethnic minority populations.[4]

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 intergenerational exposure to multiple stages of the U.S. criminal justice system. We address three primary shortcomings in prior estimates, accounting for: (1) multiple forms of exposure beyond just incarceration, (2) cumulative exposure over childhood relative to point-in-time exposure given evidence of long-term scarring from justice contact, and (3) sources of intergenerational 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 residency crosswalks that incorporate a range of novel data linkages: decennial census and American Community Survey household rosters, IRS Form 1040 tax returns, Social Security registration information, and roster information from Housing and Urban Development, Indian Health Service, and Medicare beneficiaries.

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

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 intergenerational exposure in the population, much less demographic, spatial, and temporal differences within the population.

[3]For example, see Bumpass (1990), Cherlin and Furstenberg Jr (1992), Cherlin (2004), Andersson (2002), Heuveline, Timberlake, and Furstenberg (2003), Curtin, Ventura, and Martinez (2014), Smock and Schwartz (2020), Raley and Sweeney (2020), and Cavanagh and Fomby (2019).

[4]See Cherlin and Furstenberg Jr (1992), Lichter et al. (1992), Bumpass and Lu (2000), Raley and Wildsmith (2004), Fomby and Cherlin (2007), McLanahan and Percheski (2008), Isen and Stevenson (2010), Kreider and Ellis (2011), Raley, Sweeney, and Wondra (2015), and Parker, Sassler, and Tach (2021).

are 20%, 35%, 42%, and 62%.[5] 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.

We investigate how these new measures correlate with several measures of child well-being (e.g., household poverty, behind age-appropriate grade level, cognitive difficulty, teenage parenthood, teenage criminal justice involvement, and death) 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. Heterogeneity analysis suggests differential sensitivity to exposure by child's gender and household income. Our results suggest that our new broader measures of justice exposure are as important as the smaller, more narrowly defined traditional measures from the literature, and may contribute meaningfully to propagating economic inequality and racial inequities across generations in the U.S.

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.[6] These expanded measures fundamentally redefine the scope of the spillover population in this literature, shifting the narrative from less that one-in-forty to almost one-in-two minors in the U.S. Moreover, our newly documented relationships between intergenerational exposure and child development highlight the potential unintended consequences of recent crime and social policy onto the most vulnerable members of society, in ways that undermine children realizing their full potential.

2 Why intergenerational exposure matters for children

Intergenerational 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, in addition, a second channel arises since intergenerational exposure also

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

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

represents 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 (Medicine and Council 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, Florence, and Klevens 2018).

In addition, charges may reflect adult conduct, apart from the child, that still may put the child at risk. These might include 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 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, Mueller-Smith, and Rossin-Slater 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).

Together, these scenarios capture a variety of serious and consequential experiences that children may confront. 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, Evans, and Beckett 2010; Martin et al. 2018; Finlay et al. 2022), or internal strife if charges revealed behavior that had otherwise 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, Stroud, and Buka 2016; Persson and Rossin-Slater 2018) to elementary (Sharkey et al. 2012) and high school (Sharkey 2010; Ang 2020) aged children, stress has been shown to impede physical and cognitive development and worsen educational performance (see Almond, Currie, and Duque (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, Goldin, and Yang 2018), 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 legal 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, Page, and Stevens 2011), academic performance (Dahl and Lochner 2012; T. N. Bond et al. 2021), mental health (Milligan and Stabile 2011), physical health (Aizer, Stroud, and Buka 2016), and long-term self-sufficiency (Hoynes, Schanzenbach, and Almond 2016) 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 scarring 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. Research on the causal effect of parental incarceration on children has found mixed impacts to date (Norris, Pecenco, and Weaver 2021; Arteaga 2018; Wildeman and S. H. Andersen 2017).

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, which research suggests can have important consequences for child well-being (Doyle 2007; Gross and Baron 2022).

3 Previous research

3.1 Prior attempts to measure intergenerational exposure to criminal justice

The leading estimates of intergenerational 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 (SISFCF).[7] However, these estimates are built from surveys asking about the share of inmates with minor children, which rely on assumptions about accurate sampling without non-response and attrition bias, non-overlap of any minor child among inmates, and no influence of social desirability bias in inmate responses. They also provide a point-in-time measure, which may be of limited value when trying to assess what share of children are ever exposed to parental incarceration. Using the same survey data, paired with aggregate caseload statistics and life tables methodology, which relies on strong additional assumptions, Wildeman (2009) estimates a higher cumulative exposure to incarceration at 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) a part of the AmeriSpeak panel, 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 Americans in their fifties report ever having a parent incarcerated (prison or jail).[8]

Surveys can offer advantages in the form of detailed information on social networks often omitted in administrative data, such as the nature of a caregiving relation (e.g., biological parent, stepparent, aunt/uncle, and grandparent); however, they can suffer from reporting biases, sample sizes, and often have poor coverage of the criminal justice population due

[7] These statistics are inferred from reports that 55% of individuals in 1999 and 51.9% of individuals in 2007 in state prisons reported having a minor child and 63% and 62.9% of individuals in federal prisons in 1999 and 2007.

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

to low residential stability (Roman and Travis 2004), low educational attainment (Harlow 2003), and membership in racial and ethnic minority groups (Carson and Anderson 2016).

An emerging literature has sought to study intergenerational 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 L. H. Andersen 2015), where integrated administrative data systems to support research and statistical reporting are among the most advanced in the world. At the same time, the informativeness of these findings for U.S. policy 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, Pecenco, and Weaver (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, Pecenco, and Weaver (2021) report that 38.2% of defendants in Ohio are linked to children through birth certificates. Birth certificates capture biological parent links, but 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 65% of Michigan birth certificates (1993–2006) (Norris, Pecenco, and Weaver 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. As Sykes and Pettit (2014) point out, there is an added complexity to measuring parental contact with the criminal justice system, using either survey responses or birth records, due to evolving household structures and multiple partnerships, particularly among those directly and indirectly interacting with the criminal justice system.

3.2 Changing household structures and implications for measuring caregivers

Household formation and structure in the U.S. has undergone significant transformations over the past half century,[9] with important heterogeneity by race.[10] First, there has been a

[9]See Bumpass (1990), Cherlin and Furstenberg Jr (1992), Cherlin (2004), Andersson (2002), Heuveline, Timberlake, and Furstenberg (2003), Curtin, Ventura, and Martinez (2014), Smock and Schwartz (2020), Raley and Sweeney (2020), and Cavanagh and Fomby (2019).

[10]Cherlin and Furstenberg Jr (1992), Lichter et al. (1992), Bumpass and Lu (2000), Raley and Wildsmith (2004), Fomby and Cherlin (2007), McLanahan and Percheski (2008), Isen and Stevenson (2010), Kreider

notable decline in marriage rates. Between 1980 and 2012, the percentage of women aged 40–44 who had ever married decreased by 7.9 percentage points for White, non-Hispanic women, 26.3 percentage points for Black, non-Hispanic women, and 10.6 percentage points for Hispanic women (Raley, Sweeney, and Wondra 2015; Kreider and Ellis 2011). At the same time, there has been a dramatic increase in the share of births for unmarried women, increasing from less than 5% to roughly 40% from 1940 to 2010 (Curtin, Ventura, and Martinez 2014). The composition of unmarried births also appears to be changing with the share of cohabiting partners among unmarried births increasing by 17 percentage points over the first decade of the 2000s; this is echoed by the increasing share of unmarried births with paternal information on birth records in Michigan between 1993 and 2006 (Almond and Rossin-Slater 2013), reflecting shifts in the composition of unmarried births and societal norms and policies pertaining to reporting paternity information (Rossin-Slater 2017; Massenkoff and Rose 2020).

There have also been significant increases in the number of divorces, partner separations, and second families.[11] For example, the ten-year marriage survival rate decreased by 8 percentage points for women married between 1990 and 1994 relative to two decades earlier (Kreider and Ellis 2011). And married women are 10 percentage points more likely to be on their second or subsequent marriage in 2013 relative to 1960 (Livingston 2014); however, other forms of re-partnering, such as cohabitation, are more common in recent decades and among women from racial and ethnic minorities. In fact, Kreider and Ellis (2011) estimate that over 7% of children live with a cohabiting or legal stepparent.

Finally, multigenerational households in the U.S., with grandparents functioning as caregivers, are increasingly common.[12] In 2012, 3.8% of adults 30 and over in the U.S. were grandparents living with minor grandchildren and 38.8% of those grandparents have primary responsibility for the coresident grandchildren, with substantial heterogeneity by race and ethnicity (Ellis and Simmons 2014).[13]

These changes have important implications for *which* caregivers are important to track and *how* they can be observed. Declining marriage rates and increasing non-marital romantic cohabitation heightens the need to consider relationships that are less legally formal, particularly in households with children from racial and ethnic minorities (Raley and Wildsmith

and Ellis (2011), Raley, Sweeney, and Wondra (2015), and Parker, Sassler, and Tach (2021).

[11]See Sweeney (2010), Kreider and Ellis (2011), Isen and Stevenson (2010), Raley and Sweeney (2020), Schoen and Standish (2001), Bramlett and Mosher (2001), and Teachman (2008).

[12]See Landry-Meyer and Newman (2004), Hayslip and Kaminski (2005), Choi, Sprang, and Eslinger (2016), and Williams (2011).

[13]Corresponding estimates by race and ethnicity for the share of adults defined as grandparents and the percentage with primary caregiver responsibility are: White (3.1%, 39.9%), Black (5.9%, 47.6%), American Indian/Alaska Native (7.5%, 54.0%), Asian (5.9%, 15.3%), and Hispanic (7.2%, 30.9%).

2004). Increasing divorce rates and declining relationship stability motivate greater study of intergenerational relationships that may no longer be coresident.

Increases in births to unmarried adults and decreases in the rate of paternity reporting has lowered the share of men observed on birth record data. Similar dynamics yield declining rates of paternal coverage in IRS tax filings, since only legally married individuals can jointly file and claim children. Snapshots of family composition at a given point in time, as commonly observed in household survey collections like the decennial census, fail to capture evolving household structure as romantic partners and other adult caregivers leave and join the households of children over time.

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

Currently, no single dataset in the U.S. captures all the potential intergenerational influences a minor interacts with in 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,[14] together they provide an opportunity to measure the population in unprecedented ways. 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, including successful replications of recent fertility estimates from the National Center for Health Statistics and National Vitality Statistics System, can be found in Appendix B.[15]

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.[16] When multiple addresses

[14]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 10 years.

[15]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 (B. Bond et al. 2014), this project minimizes possible linkage bias by combining data from many sources.

[16]We harvest residential addresses from the following data source: decennial censuses (2000, 2010), Amer-

are identified for an individual in a given calendar year, priority is given first to Census Bureau surveys, then to tax records, and then to public program data.

The residence crosswalk functions as the "backbone" of the relationship crosswalk. First, for each year, all coresident individual pairs are identified.Where possible, these cohabiting relationships are further delineated into specific relationship types based on information from the 2000 and 2010 decennial censuses, 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. Because of data limitations, 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 Figure A1 for sample composition descriptives).[17]

Figure 1 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. 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 Figure A3), which could be due to a variety of living circumstances: (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. These estimates reflect how common it is currently for children in the U.S. to grow up with multiple adult influences in their households beyond the traditional notion of the nuclear family with one mother and one father. Further discussion of these results, particularly by racial subgroup, can be found in Appendix B.

Adult experiences in the criminal justice system are measured using CJARS, which covers 23 states with over 175 million unique events spanning multiple procedural stages of

ican 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/state level information from Medicare (2000–2017 EBD) and Medicaid (2000–2014 MSIS) enrollment databases, Indian Health Service (IHS) from 1999–2017, and the Master Address File-Auxiliary Reference File (MAF-ARF) (2000–2018).

[17]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 intergenerational exposure rates have changed over time.

the justice system (e.g., arrest, charge, conviction, incarceration, and/or parole) with some jurisdictional data spanning 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 through age 18. Sufficient coverage is available to study 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, within the period when our focal children were born. Likewise, sufficient statewide coverage is available to study prison incarceration in Arizona, Florida, Michigan, Nebraska, North Carolina, Pennsylvania, Texas, Washington, and Wisconsin, roughly 30.3% of the population.[18,19] 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 as well as demographic and socioeconomic characteristics. Thus, we believe the estimates in this paper generalize nationally.

5 Novel estimates of intergenerational exposure to criminal charges, convictions, and incarceration

In this section, we report our overall findings on the extent of intergenerational exposure of children to charges, convictions, and incarceration. To align with 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 intergenerational exposure to arrive at our most comprehensive measures of the share of children in the U.S. who experience the justice system secondhand through the 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 of intergenerational exposure to the criminal justice system: 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

[18] For a full description of CJARS including a code book and location specific coverage, see Finlay and Mueller-Smith (2020).

[19] Jail records are currently not included systematically in CJARS.

equation:

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

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 the place of birth is no longer covered by CJARS.[20] 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 2A, we document that 0.8% of children in our sample have a biological parent in prison in a given year during their childhood,[21] with 0.3% having a parent enter prison in a given year. 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 intergenerational exposure in a given year. Instead, we need to identify how many ever experience 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:

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

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 2B (solid lines) presents the share children ever exposed by age τ, where $\tau \in [0, 18]$, to a biological parent 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

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

[21]This number 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 Federal and State 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.

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).[22]

Cumulative exposure over the age profile throughout childhood (ages 0 to 18 years old) grows steadily. Because our focus is on extensive-margin exposure, 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.

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.[23]

In Figure 2C, we report 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 intergenerational 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 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 intergenerational exposure measures are 958%, 1881%, 1693%, and 964% higher for exposure

[22]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 L. H. Andersen (2015) use life tables and the Survey of Inmates of 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).

[23]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.

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 years old is more consistent year-over-year compared to exposure rates focused just on biological parents (see Figure 2B 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 are having repeated contact with the criminal justice system over their childhood, which we refer to as the intensive margin of exposure.

Figure 2D 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 marginal 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.[24] 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 2B, 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 childhoods.

6 Socioeconomic variation in exposure and discussion

In this section, we dig further into the findings of Section 5, disaggregating cumulative exposure rates by age 18 from any potential adult caregiver by the child's race and ethnicity, family income at birth, and the potential caregiver's sex. In addition, we present evidence on the share of exposure that occurs after the adult in question has coresided with the child.

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 3A, 62% of Black,

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

non-Hispanic (referred to as Black for the remainder of Sections 6 and 7) children grow up in a household where one or more potential caregivers are charged with either a misdemeanor or felony criminal offense.[25] 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 Sections 6 and 7) and Asian children have high but relatively lower rates of intergenerational exposure to criminal charges at 32% and 17% respectively. Exposure rates decline for more serious forms of criminal justice contact, but remain alarmingly 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.[26,27]

Racial and ethnic disparities increase with the seriousness of exposure type. The ratio of exposure among children from racial and ethnic minorities[28] relative to White children grows by level of exposure: any criminal charges (1.40–1.90), felony charges (1.57–2.59), felony convictions (1.63–2.53), and prison (1.86–3.23). Such disparities raise important questions about the potential role the U.S. criminal justice system plays in propagating economic inequality, racial inequities, and limiting social mobility across generations.

Important differences by race and ethnicity are also clear when examining the intensive margin of exposure (see Figure A7). For example, the marginal median exposed Black child grows up in a household with 6 criminal charges, 3 felony convictions, and 5 years of adult incarceration. In fact, among Black children who are exposed to at least one criminal charge in their household, 34% experience 10 or more criminal charges during their childhoods. In contrast, the median White child grows up in a household with 3 criminal charges, 2 felony convictions, and 4 years of adult incarceration; only 16% experience 10 or more charges during their childhood conditional on being exposed.

Exposure by household income rank. Figure 3B documents changing exposure risk

[25] 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.

[26] For comparison, Wildeman (2009) uses the Survey of Inmates of State and Federal Correctional Facilities, the National Corrections Reporting Program and life-table methodology to estimate that 25–28% (13.8–15.2) of Black children and 3.6–4.2% (2.2–2.4) of White children born in 1990 (1978) are exposed to a parental incarceration by the age of 14 (see Table 3 of their paper).

[27] See Appendix Figure A4 for additional results that compare differences in cumulative exposure from just biological parents by child's race. For example, the share of Black children exposed to an incarceration, felony conviction, felony charge and any criminal charge increases by 55%, 100%, 118% and 180% respectively when incorporating other potential caregivers into their potential sources of intergenerational exposure in addition to biological parents, a higher increase compared to White children which reflects the important differences in household structure by race as noted earlier in Figure 1.

[28] In this context, we define racial and ethnic minorities to include Black, Hispanic, and American Indian/Alaska Native children.

over the household income distribution, as measured at birth and in the following 4 years.[29] 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). 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 parental income, and 440–2950% higher than children born at the 90th percentile of parental income. While any charges remains 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 felony charges, felony convictions, or incarceration.

Figure A8 separates out the relationship between household income and criminal justice exposure, by the child's race and ethnicity.[30] Across all types of exposure that we consider, there remain stark exposure gaps by race conditional on income rank. Black and American Indian/Alaska Native children remain consistently 10–20 percentage points higher than White children, conditional on income. The experience of Asian children is quite remarkable, where we observe consistently low rates of contact across the entire income distribution. Finally, the relationship to household income varies by race. Hispanic children begin with lower exposure rates than White children; however, this relationship is reversed by the 40th percentile of household income.

Exposure by sex of potential caregiver. Figure 3C depicts the cumulative exposure rates by age 18 by the sex of the potential caregiver in the household. The vast majority (over four-fifths) of children with intergenerational exposure (at all levels of severity) observe 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 exclusively comes from male potential caregivers, while

[29] To construct this exercise, we linked children to tax filings for which they are claimed as a dependent during the first 5 years of their lives. We average over total income and rank households within child birth years. Exposure is then calculated within each individual percentile. 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 not included.

[30] Note that White refers to White, non-Hispanic and Black refers to Black, non-Hispanic throughout Sections 6 and 7.

only 53% of criminal charge exposure exclusively comes from male potential caregivers.[31,32,33]

Offense types. Adult criminal charges provide a window into the potential living circumstances of the most vulnerable children. Criminal charges include a range of risky and dangerous behaviors, like violence and substance abuse, and may indicate material need (e.g., theft, fraud), both of which are not conducive to child development.

In Figure 4A, we disaggregate the cumulative exposure rates by age 18 by the nature of the criminal charge, including: violent, property, drug, driving under the influence (DUI), other criminal traffic, and public order.[34] 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 criminal charges. In addition, 16% have adults in their household face illicit drug charges at some point during their childhood.

Racial disparities previously discussed carry over to exposure by offense type as well (Figure 4B). Roughly one-in-three Black and American Indian/Alaska Native children have an adult in their household face violent criminal charges, while the corresponding estimate for White children is only one-in-eight. Relative to the distribution of offense types for exposed White children, exposed Black children are more likely to grow up in households with drug charges and less likely to witness DUI offenses. Exposed Hispanic children are less likely to experience other criminal traffic offenses. Finally, exposed American Indian/Alaska Native children are less likely to have adults charged with property offenses but more likely for public order offenses to have occurred.

Exposure to all offense types declines across the income distribution (Figure 4C). The largest decline is observed for property offenses, which aligns with the fact that many offenses categorized as property are financially motivated. These are followed closely by drug, violent, and public order offenses. The offense type with the smallest decline across the income distribution is DUI, making it relatively much more common among affluent households with involvement in the justice system.

Incidence of exposure during recent coresidency with potential caregiver. A concern that can be raised regarding the estimates presented so far relates to whether the

[31]In Appendix Figure A4, we see relatively less sex differences in exposure for biological parents, although the same qualitative pattern remains. This is likely due to differences in our ability to link children to their biological parents by sex of the parent, which are not as stark for more inclusive definitions of adults who contribute to intergenerational spillovers.

[32]For comparison, Wildeman and L. H. Andersen (2015) uses the Survey of Inmates of State and Federal Correctional Facilities and life-tables and 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 (see Table 3 of their paper).

[33]Additional results by child race and potential caregiver sex in Appendix Figure A5.

[34]See Appendix Table B4 for detailed information on the most commonly occurring offenses within each of these broader categories.

observed caregiver is still in the child's life in a meaningful way at the time of the criminal justice exposure (Norris, Pecenco, and Weaver 2021). If it has been years since the adult had any real connection with the child, should this be counted as a valid intergenerational exposure?

To address this question, we document the cumulative exposure based on whether the event happened when the adult in question was recently living in or out of the same home as their child. Specifically, we measure coresidence between the potential caregiver and child and consider the event to occur while the adult is "in the home" if they lived together in the year of the event or either of the two years prior. Residence is observed quite well for the population in Decennial Census years or if individuals file taxes, respond to the ACS, or are enrolled in a public program[35] in the relevant years.

We find that the share of children exposed to a potential caregiver in prison, receiving a felony conviction, felony charge, or any criminal charge decreases by 46%, 35%, 33%, and 21%, respectively, when restricting to exclusively "recent coresidency" exposures (Figure 5A). The majority of cumulative exposure, however, is by adults recently coresiding in the home. And in fact, the largest decrease in exposure based on the recent coresidency restriction is for incarceration, which often occurs after several prior criminal justice interactions have occurred (e.g., prior arrests, convictions, and pre-trial detention) that might cleave the individual from their family unit. Figure 5B shows the corresponding figure restricting to exposure originating from exclusively biological parents; here we see qualitatively the same story, with the majority of exposed children experiencing at least one event with recent coresidency across all exposure types. These results are remarkably consistent with statistics from the Survey of Inmates: 36% of fathers and 59% of mothers cohabitate with their minor children prior to incarceration (Mumola 2000). Consistent with our examination of the intensive margin of exposure, many children are also exposed to out-of-home events, especially for more serious forms of exposure. This also reflects the evolving nature of household composition for children growing up in the United States.

However, there are many channels through which exposure by a caregiver may indirectly affect children, even if not currently or recently coresiding at the time of the criminal justice event. Given the high divorce and separation rates in the U.S., it is very possible that children still have significant contact with a biological parent that does not live in the home (Cancian and Meyer 1998). Moreover, child support payments often follow parents regardless of whether they coreside with their child or not (Amato and Gilbreth 1999). Thus, criminal justice involvement may harm the finances of the child's home even if the parent is not

[35] This includes HUD, Medicare, and IHS. Medicaid records at the Census Bureau do not contain address-level information on enrollees.

currently living in the home.

For potential caregivers, note that exposure is not counted until we observe the caregiver coresiding with the child. Thus, a stepparent or unclassified caregiver with a criminal justice event prior to entering the household will not count as exposure during childhood to the criminal justice system. We view this choice as conservative since pre-existing convictions, for example, may continue to inhibit adult labor market success once cohabitation begins, resulting in indirect impacts to the child.

Decomposing the determinants of exposure. To further explore the determinants of the racial exposure gaps, we conduct a series of decomposition exercises in the style of Blinder (1973) and Oaxaca (1973) which are presented in Figure 6.[36] For each major type of exposure (charges, felony charges, felony conviction, and incarceration), we evaluate the role of observable differences between White children and Black, Hispanic, and American Indian/Alaska Native children in explaining the overall gap. The exercises consider the relative influence of county of birth, household income, and household structure (i.e., the number of male and female, bio and non-bio adult links in the child's life).

County of birth appears to play a minor role. For the White-Black comparison, if anything, the racial gap would be larger if White and Black children were equally distributed across places of birth. Similar conclusions can be drawn from the White-American Indian/Alaska Native decomposition. The White-Hispanic gap, however, does appear to potentially partially attributable to difference in county of birth, explaining roughly 7% to 27% of the raw gap.

When we add household income around the time of the child's birth into the decomposition, a more substantial share of the raw gap across all minority groups is explained by observable characteristics.[37] Conditional on county of birth, household income explains approximately 17% to 42% of the raw racial gap, depending on the specific type of exposure and minority group under consideration.

The final observable trait we consider is household structure. The number of adults that a child is linked with will obviously influence the likelihood of exposure to the justice system, but at the same time, because this trait is realized over the course of their childhood, it may be endogenous. For instance, if a child's father is sent to prison, they may be more likely to be linked with additional potential caregivers either because their mother moves in with other family members or because she starts a new romantic relationship. For this reason,

[36]To execute this exercise, we estimate models for both White and non-White groups separately, and then take a population weighted average of the share of the explained variation stemming from observable characteristics.

[37]Household income is measured using the average AGI reported on the IRS Form 1040 that the child was claimed on in their year of birth and subsequent four years.

these estimates should be evaluated with caution.

Household structure appears to play an important role in exposure to the justice system. Conditional on county of birth and household income, realized household structure may explain an additional 30% to 54% of the raw racial exposure gaps.[38]

After accounting for these three factors, almost the entire White-Hispanic gap is accounted for by observable characteristics. Likewise, about half to three quarters of the White-American Indian/Alaska Native gap is explained by observable differences between the racial groups. However, only about 50% to 60% of the White-Black gap is explained by these characteristics, leaving a substantial portion of the differential unexplained. But, because realized family structure is endogenous, the shares explained by observable differences are likely overstated for all groups.

7 Estimating the relationship between intergenerational exposure and markers of childhood well-being

So far, we have documented profoundly high rates of intergenerational exposure to the U.S. criminal justice system; for example, more than one in two Black children grow up in households where an adult has faced criminal charges during their childhood. But, how these broad measures of intergenerational exposure actually impact child development and well-being remains unanswered.

It is entirely possible that less serious types of justice involvement (e.g., a criminal charge versus prison), less meaningful adult-child relationships (e.g., an adult roommate versus a biological parent), or less recent incidents of exposure are less impactful for children and/or signal less about their environment. If true, the broad measures we introduce may not be so dire. While we have documented new evidence on the reach of the justice system within American households, researchers and policymakers would need to look further if the ultimate goal is to understand and address the determinants of economic inequality and racial inequities in the U.S.

However, evidence showing that these less studied and more common forms of intergenerational exposure to the justice system are harmful to children would raise serious concern. Without remediation efforts, even a complete overhaul to American social policy to limit intergenerational justice exposure going forward would only succeed in protecting future generations; society would still have to bear the costs of the unrealized potential of, and negative externalities from, current and former youth for decades to come.

[38]Given our concerns regarding endogeneity, an alternative interpretation of these statistical relationships is that the justice system has significant impacts on relationships, family stability, and living arrangements.

Establishing causal evidence uncontaminated by endogeneity bias on each of the dimensions of variation that we highlight (contemporaneous versus cumulative exposure, biological parent versus all potential caregiver exposure, prison versus other justice events exposure) is beyond the scope of this paper. Instead, we tackle a less perfect, but more realistic empirical goal that we believe still yields valuable insight, noting that prevailing views of selection in the literature would suggest that contemporaneous incarceration of biological parents should be the most strongly correlated with negative outcomes for children.

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) as well as to administrative data on teen fertility (our relationship crosswalk), adult criminal justice contact through age 19 (CJARS), and mortality through age 19 (Census Numident). 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.[39] We then examine the relative correlation between various definitions of intergenerational exposure to the justice system and child outcomes. The outcomes we consider include: (1) household-level variables—a child's household poverty status and whether a grandparent has primary responsibility for their care; (2) human capital development measures—whether the child is behind in school given their age, has difficulty concentrating, remembering, or making decisions, and whether they have dropped out of high school; and, (3) other teenage outcomes—are they a teen parent, have they been criminally charged in the adult system as a teenager, and did they die by age 19.

We estimate naive regressions without any controls showing the raw correlation between each specific type of exposure and the outcome, as well as joint exposure specifications in which we control for a third order polynomial in household income at birth, age-at-survey fixed effects (γ_{age}), fully saturated sex by race/ethnicity fixed effects ($\gamma_{race,sex}$), survey-year fixed effects (γ_t), place-of-birth fixed effects (γ_{geo}), and year-of-birth fixed effects (γ_{by}), as

[39] 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 (see an example form here: `https://www2.census.gov/programs-surveys/acs/methodology/questionnaires/2020/quest20.pd`). For teenage outcomes based on administrative data, we define contemporaneous exposure as being exposed between the ages of 15 to 18, and prior exposure as ages 0 to 14 years old.

reflected in our estimating equation below.[40]

$$
\begin{aligned}
Outcome_{i,t} = {} & \beta^{bio,curr} I(\text{Bio-parent exposure})_{i,t} + \beta^{other,curr} I(\text{Other adult exposure})_{i,t} \\
& + \beta^{bio,cum} I\left(\sum_{\tau=by}^{t-1} \text{Bio-parent exposure}_{i,\tau} > 0\right) \\
& + \beta^{other,cum} I\left(\sum_{\tau=by}^{t-1} \text{Other adult exposure}_{i,\tau} > 0\right) \\
& + \phi_1 \text{HH Income} + \phi_1 \text{HH Income}^2 + \phi_1 \text{HH Income}^3 \\
& + \gamma_{age} + \gamma_{race,sex} + \gamma_t + \gamma_{geo} + \gamma_{by} + \epsilon_{i,t}
\end{aligned}
$$

To the extent that omitted variables bias contaminates our regression coefficients, one would expect this to lead to relatively worse "impacts" associated with contemporaneous incarceration of biological parents. 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, for example: their coresiding uncle who was once charged with possession of marijuana when they were 2 years old.

Main results. Figure 7 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 raw correlations without controls are presented offset from the main results for comparison purposes.[41]

The estimated relationship between exposure and household poverty status (Panel A) is remarkably similar after controlling for the observable characteristics described above. Whether exposure reflects charges or incarceration, bio-parents or other household members, or current or past events, the estimates consistently fall in the range of 60 to 90 percent of the non-exposed child mean, with many of the coefficients being statistically indistinguishable. These findings are consistent with the hypothesis that the negative economic impacts of the justice system on families operate through the channel of criminal records more so than incapacitation, which would mean that the impacts of the justice system are experienced by a much larger swath of the population than generally recognized (Mueller-Smith and Schnepel 2021). Whether grandparents are identified as the child's primary caregiver (Panel

[40] In addition, standard errors are clustered by the commuting zone/county of birth. Regressions are weighted by the ACS-provided person weights.

[41] Model estimates with controls can be found in Appendix Table C1. Raw correlations can be found in Appendix Table D1.

B), however, does seem to be both: (1) more intimately connected to the most serious forms of justice contact like felony convictions and incarceration, and (2) be most strongly associated with the justice involvement of biological parents over other household members. This clear pattern aligns with the legal processes in place for child welfare investigations, child removal, and resulting kinship care placements.

The next three panels show a strikingly similar pattern of evidence regarding human capital formation during childhood. Whether considering being behind age-appropriate grade level (Panel C), whether the child has shown signs of difficulty concentrating, remembering, or making decisions (Panel D), or having dropped out of high school as a teenager (Panel E), 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. This suggests that some sort of social, emotional, or other scarring effects may be at work, and highlights the importance of tracking cumulative exposure among children, which can be 10 times larger than point-in-time estimates of contemporaneous exposure.

Teenage outcomes, that leverage administrative data on the full population,[42] are the final outcomes we consider.[43] Teen parenthood (Panel F) follows a pattern most typically associated with popular conceptions of the justice system: that current incarceration of a family member has the largest impact on children. Interestingly, whether the source of the exposure stems from a biological parent or another potential caregiver is statistically indistinguishable, likely reflecting the departure many U.S. households have made from the traditional nuclear family and the importance for children of non-biologically related adults in their household.

The largest effects of exposure on being charged with an adult crime[44] (Panel G) stem from contemporaneous bio-parent justice involvement, regardless of the specific type of justice involvement. The estimated coefficients are roughly 3 times the size of the non-exposed child mean. Other forms of exposure (other potential caregivers, prior exposures) remain meaningfully high in the range of 1.5 to 2 times the non-exposed mean and are mostly statistically indistinguishable.

Finally, teenage death (Panel H) follows a similar pattern to what we observed for educational outcomes. Cumulative exposure tends to have the largest and most precise effect

[42]In this exercise, we exclude all observation that died prior to reaching age 12.

[43]Model estimates with controls can be found in Appendix Table C12. Raw correlations can be found in Appendix Table D2.

[44]CJARS does not include data from the juvenile justice system, and so we are precluded from measuring all criminal charges that might be occurring for these individuals.

on mortality, especially for the most serious forms of justice involvement. If this relationship were purely mechanical (because the child had been killed by an adult household member), the estimated relationship should principally load on contemporaneous exposure to felony convictions and incarceration, which is not what we observe.[45]

Heterogeneity analysis. The impact of intergenerational exposure to the justice system likely varies by a child's background. In Figure 8, we further probe the relationship between exposure and child well-being through subgroup analysis along three dimensions: (1) race/ethnicity, (2) sex, and (3) household income rank at birth. For the sake of simplicity, we restrict ourselves to the broader form of exposure (any criminal charge) with control variables for a select set of outcomes, but the full set of results for all potential specifications can be found in Appendix Tables C1–C22.

In Figure 8A, we see what appears to be an inverse relationship between the underlying non-exposed mean and the estimated coefficient on exposure of having a grandparent as a primary caregiver. White and high-income children, who have the lowest rate of this outcome in the non-exposed population, have the largest increase given some form of exposure in the household. This suggests that there is heterogeneous capacity to leverage kinship networks to remediate negative shocks arising from crime and justice involvement among adults in the child's life that reinforces economic inequality and racial inequities.

Figure 8B shows stark differences in human capital development among exposed children by sex of the child. Boys appear to be significantly more sensitive to exposure, with estimated coefficients more than double the size compared to those for girls. Given the disparity in the originating source of exposure by the sex of the adult, it may be that boys are uniquely impacted by the justice involvement or related events of their fathers and/or father-like figures. More research is warranted to further probe this relationship.

Figures 8C and 8D continue this theme of differential effects by gender of the child. Girls, and children from middle and low income families, are especially responsive on the teen fertility outcome when after experience an exposure event. Boys, and children from middle and low income families, are much more likely to be charged with adult criminal charges after they experience an exposure event.

It is perhaps surprising that there is not clearer differentiation in the estimated effects of exposure by racial and ethnic group. However, this should not be misconstrued as indicative that the justice system does not potentially play a role in propagating racial inequities across generations in U.S. As previously documented, there are stark differences in exposure prevalences by child's race, which itself will further racial gaps even with similar responses

[45]Because we do not have access to cause of death, we unfortunately cannot differentiate between children who were killed by members of their household versus other causes of death.

among children.

8 Conclusion

There is significant concern regarding, and a large body of evidence about, how childhood conditions impact long-term outcomes. Given the wide reach of the criminal justice system in the United States, the implications of the underlying illicit behavior for child safety and household resources, and disproportionate impact among racial and ethnic minorities and low-income communities (Shannon et al. 2017), intergenerational exposure to the criminal justice system is likely an important factor in the development of many children in the U.S. and contributes to the propagation of racial inequities.

However, the scope and role of intergenerational criminal justice exposure is largely unknown due to a multitude of data limitations in the United States. First, it is difficult to measure and observe the relevant caregiver figures in a child's life, particularly in light of changing household structures over recent decades with substantial differences by racial and ethnic groups. For example, paternal information is often left off of birth records and marriage has become less common among romantic partners in recent decades, which means they do not file taxes and claim dependent children together. Second, criminal justice records are not integrated across agencies, making it difficult to observe adult criminal justice contact at the population level across geography and types of criminal justice involvement. 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 Census Bureau surveys, federal tax forms, and public program enrollment, and then link them to the newly created Criminal Justice Administrative Records System (CJARS).

Using this new data infrastructure, built and linked at the person level, we are able to produce novel measures of intergenerational exposure to charges, felony charges, felony convictions, and incarcerations. For children born between 1999 and 2005, we find that 9% of children have had an intergenerational exposure to prison, 18% have been exposed to a felony conviction, and 39% have been exposed to any criminal charge over the course of childhood, results that are much larger than previous estimates which primarily focused on parental incarceration. Our estimates highlight, for the first time, the importance of other forms of criminal justice exposure beyond incarceration, cumulative estimates that acknowledge the potential for lagged and lasting impacts from crime and criminal justice contact, and the importance of capturing diverse household structures.

We document important differences by race, which have significant implications for policies related to child well-being and persistent intergenerational inequalities. For example, Black, non-Hispanic children have the highest rates of intergenerational 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 intergenerational contact, 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.

Finally, we document strong negative correlations between intergenerational exposure to the criminal justice system and various measures of child development and well-being. These findings support the conjecture that many forms of criminal justice contact beyond contemporaneous exposure, exposure by a biological parent, and exposure to incarceration have meaningful implications for childhood environments and outcomes. The degree and expression of these negative outcomes varies by child's gender and household's income, with more limited variation by child's race (conditional on exposure). The results from these exercises strengthen the case that our broader measures of intergenerational exposure to the justice system are significant and consequential for the lives and outcomes of children. More research is warranted to further probe the causality behind these estimated coefficients, but given the scope of exposure that we identify, and the disparate racial nature of the exposure, the justice system should become a first-order issue for those interested in economic inequality, intergenerational mobility, and racial inequities. Moreover, these results heighten the need for policy accountability for factors that have contributed to such widespread intergenerational exposure to the justice system, and raise serious concern regarding the implications for future generations given the extent of intergenerational exposure, especially when concentrated among children from racial and ethnic minorities.

As more data become available, future work should consider how exposure rates have changed across temporal birth cohorts in the United States and between those born in different geographic jurisdictions. These are of particular interest given the changing landscape of criminal justice policy over the last half century and vast differences in justice policy across regions of the U.S. Such future work will be possible by leveraging the comprehensive and growing geographic coverage of CJARS and expanding linkage opportunities with increasingly available historical data (e.g., past decennial censuses).

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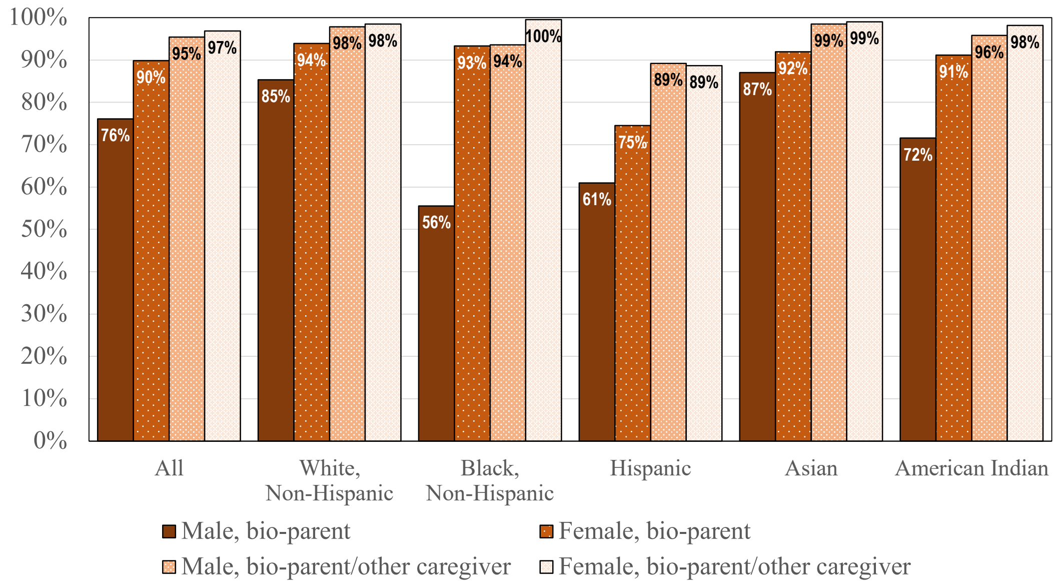
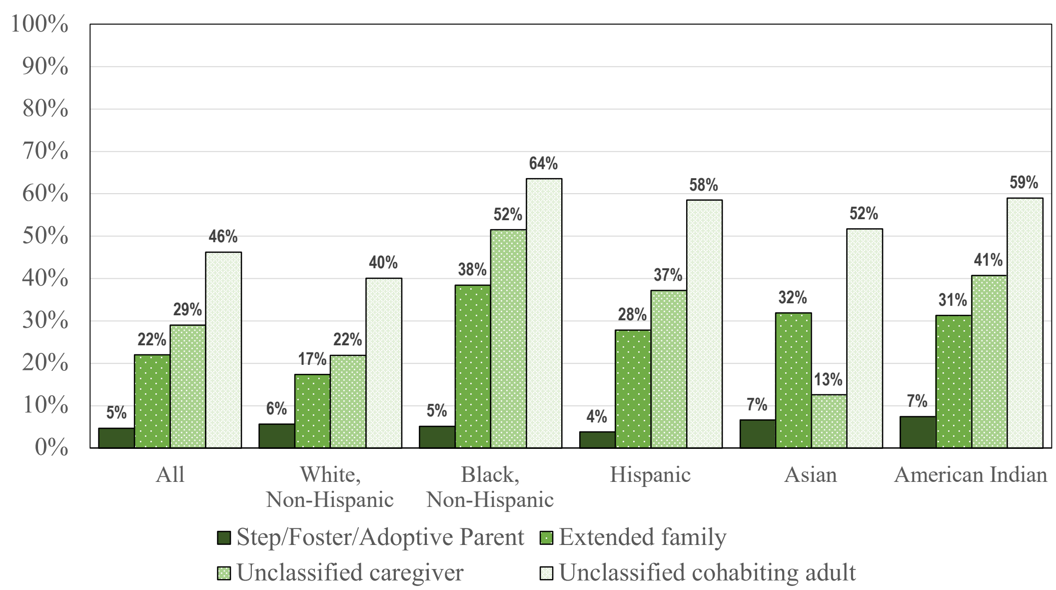
Figures and tables

Figure 1: Share of children in 1999–2005 birth cohorts with observed relation types

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



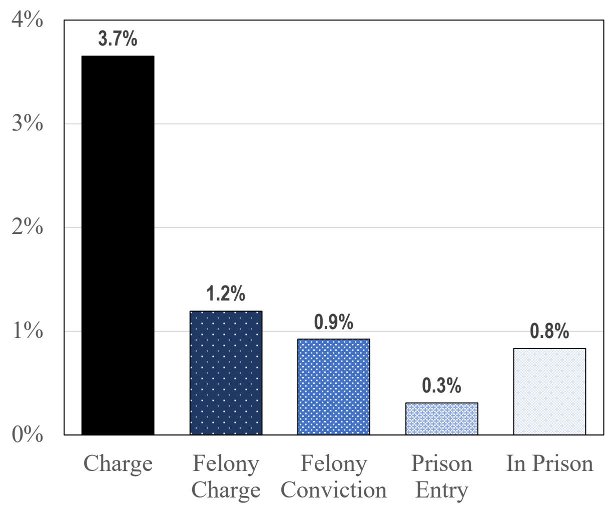
B: Share of children with specific observed potential caregiver relationships



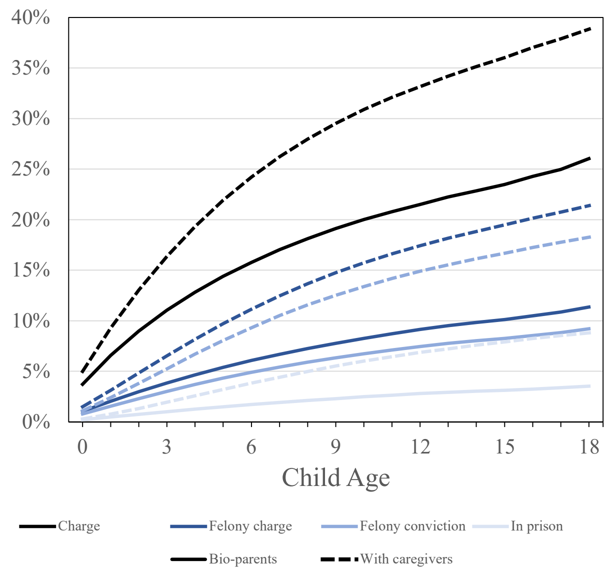
Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.
Notes: This figure depicts the types of parental relationships identified for children in Census Numident born between 1999–2005 that are identified with a potential caregiver relationship at the national level. 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 number CBDRB-FY22-ERD002-001.

Figure 2: Exposure to the criminal justice system and comparison of measures

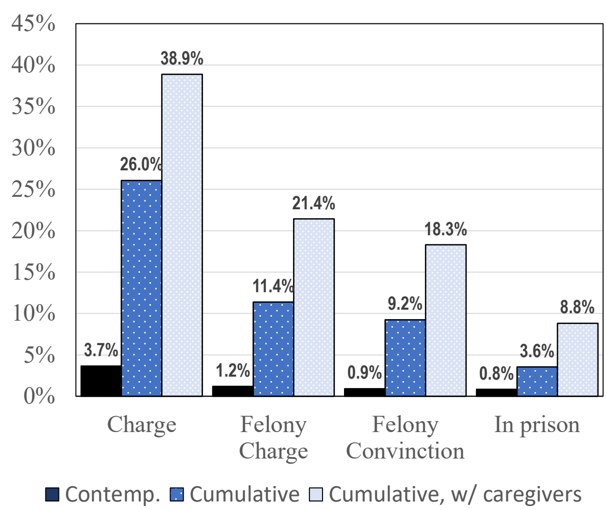
A: Contemporaneous exposure, biological parents



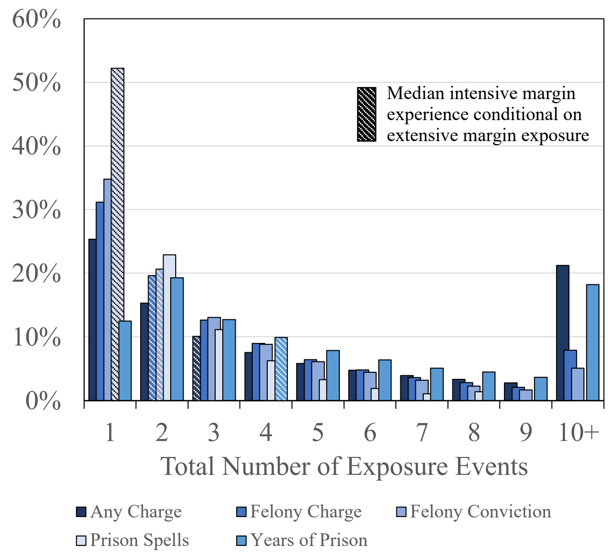
B: Cumulative exposure, biological and other potential caregivers parents



C: Comparison of exposure measures

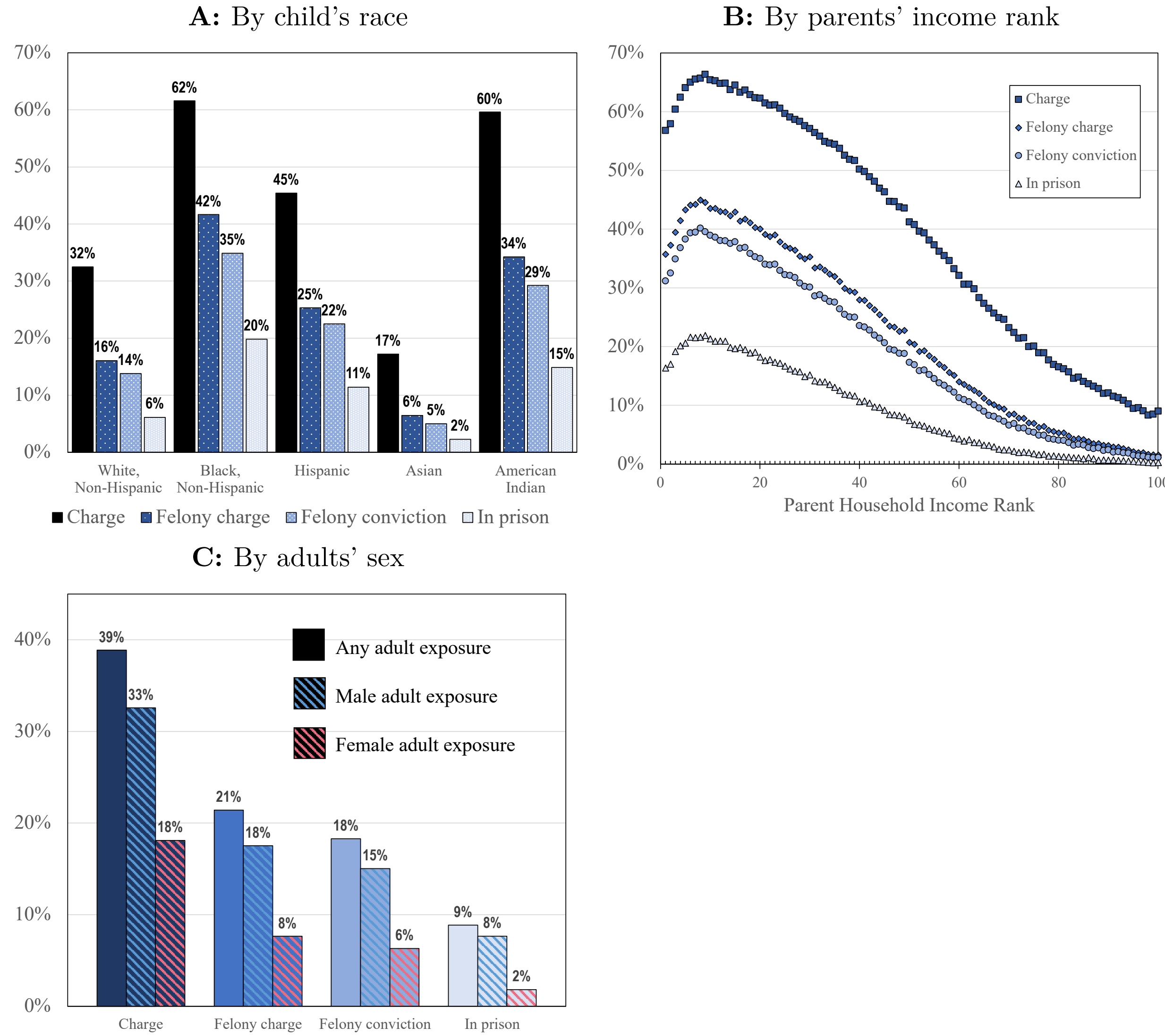


D: Intensive margin of all-source, cumulative exposure



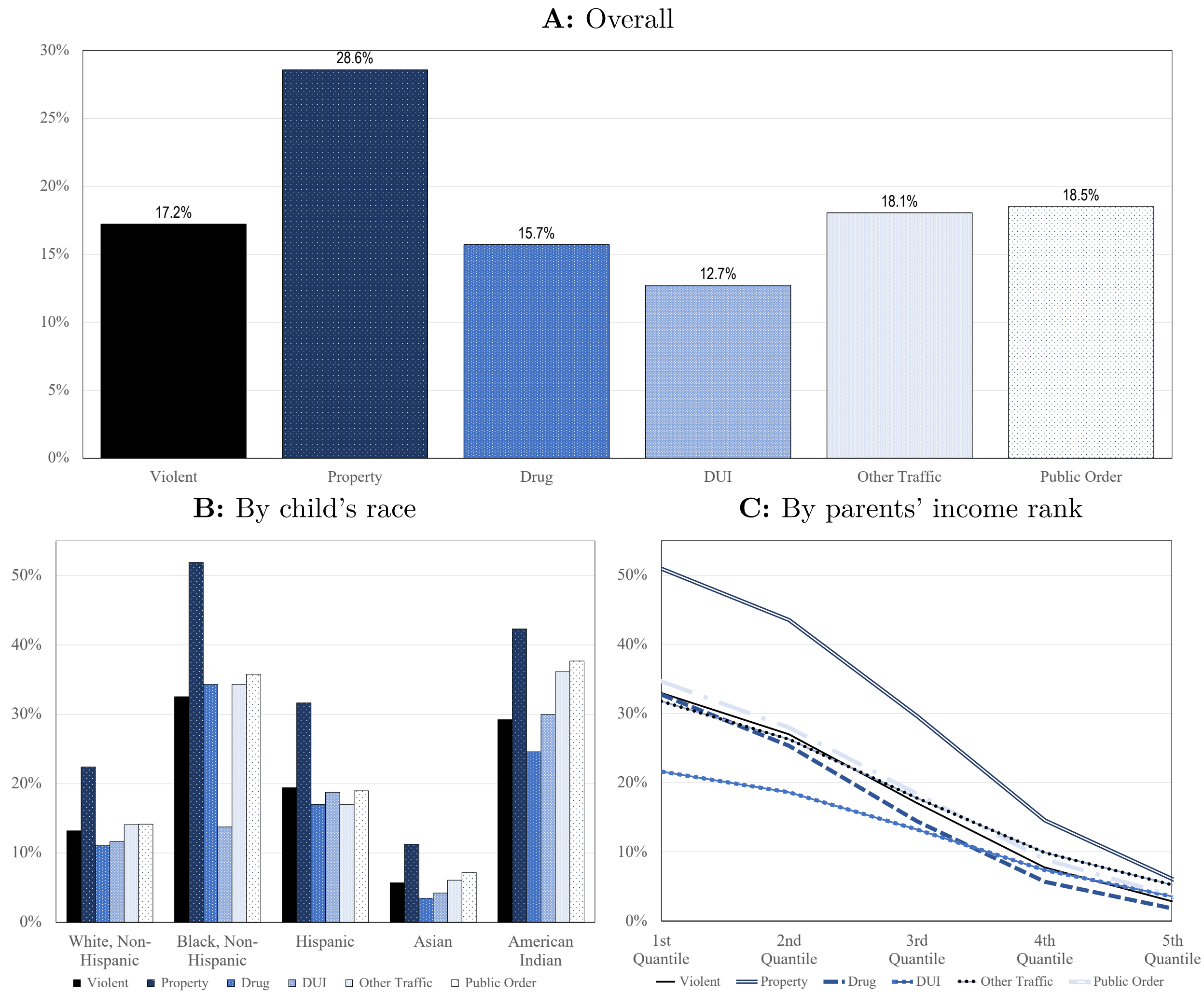
Source: Calculations are based on the Census Numident, CJARS, and the CJARS relations and residency crosswalks.
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. For Panels A, B, and C, the sample consists of individuals in the Census Numident 1999–2005 birth cohorts in 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+ years), and unclassified adult (cohabiting 2+ years). For Panel D, 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, authorization numbers CBDRB-FY22-ERD002-001, CBDRB-FY22-ERD002-003, and CBDRB-FY22-ERD002-009.

Figure 3: Heterogeneous cumulative exposure to the criminal justice system by all potential caregivers by age 18: charge, felony charge, felony conviction, incarceration



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 is depicted for children across race (Panel A), income percentile bins (Panel B), and adult potential caregivers' sex (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, authorization numbers CBDRB-FY22-ERD002-001 and CBDRB-FY22-ERD002-003.

Figure 4: Cumulative exposure to criminal charges by offense type

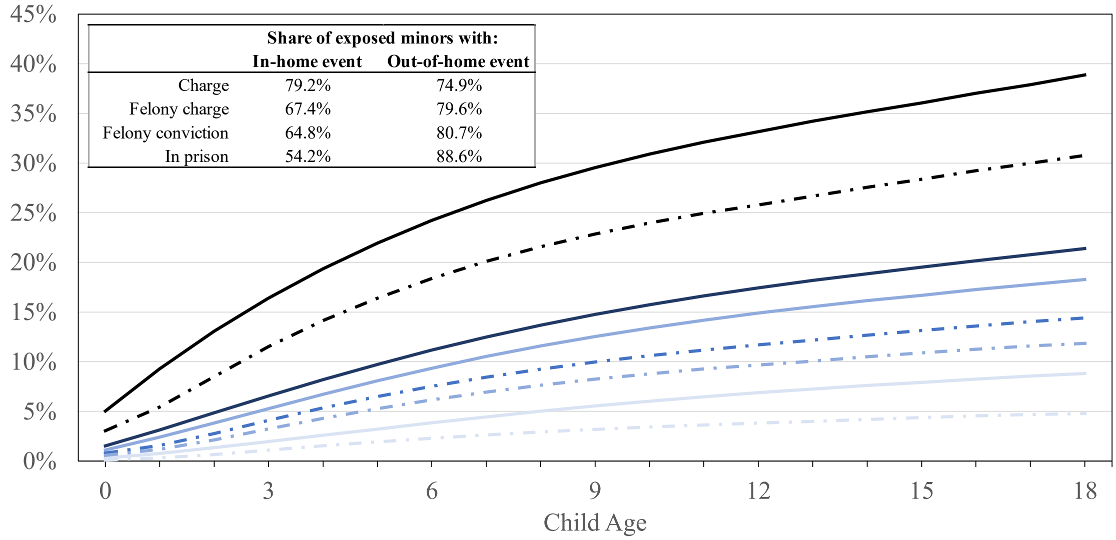


Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, the CJARS relations and residency crosswalks, and IRS Form 1040s (1999–2009 tax years).

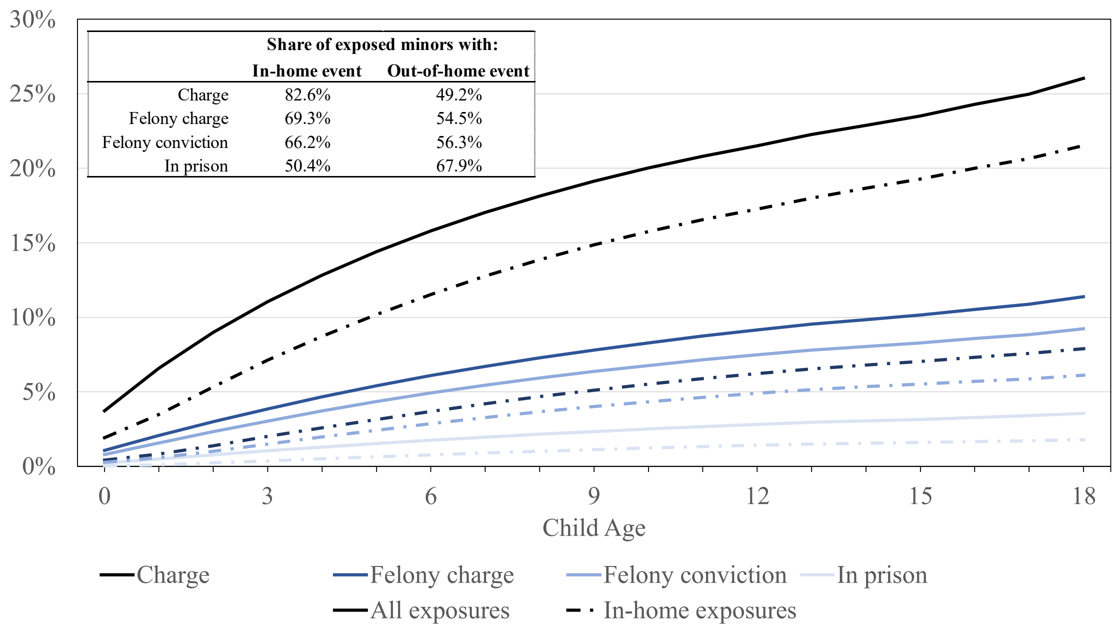
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2000 birth cohorts in CJARS-covered geographies from birth until age 18. Average exposure by age 18 to specific charge types is depicted for children overall (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, authorization number CBDRB-FY22-ERD002-009.

Figure 5: Cumulative current or recent coresidency exposure to the criminal justice system

A: All potential caregivers



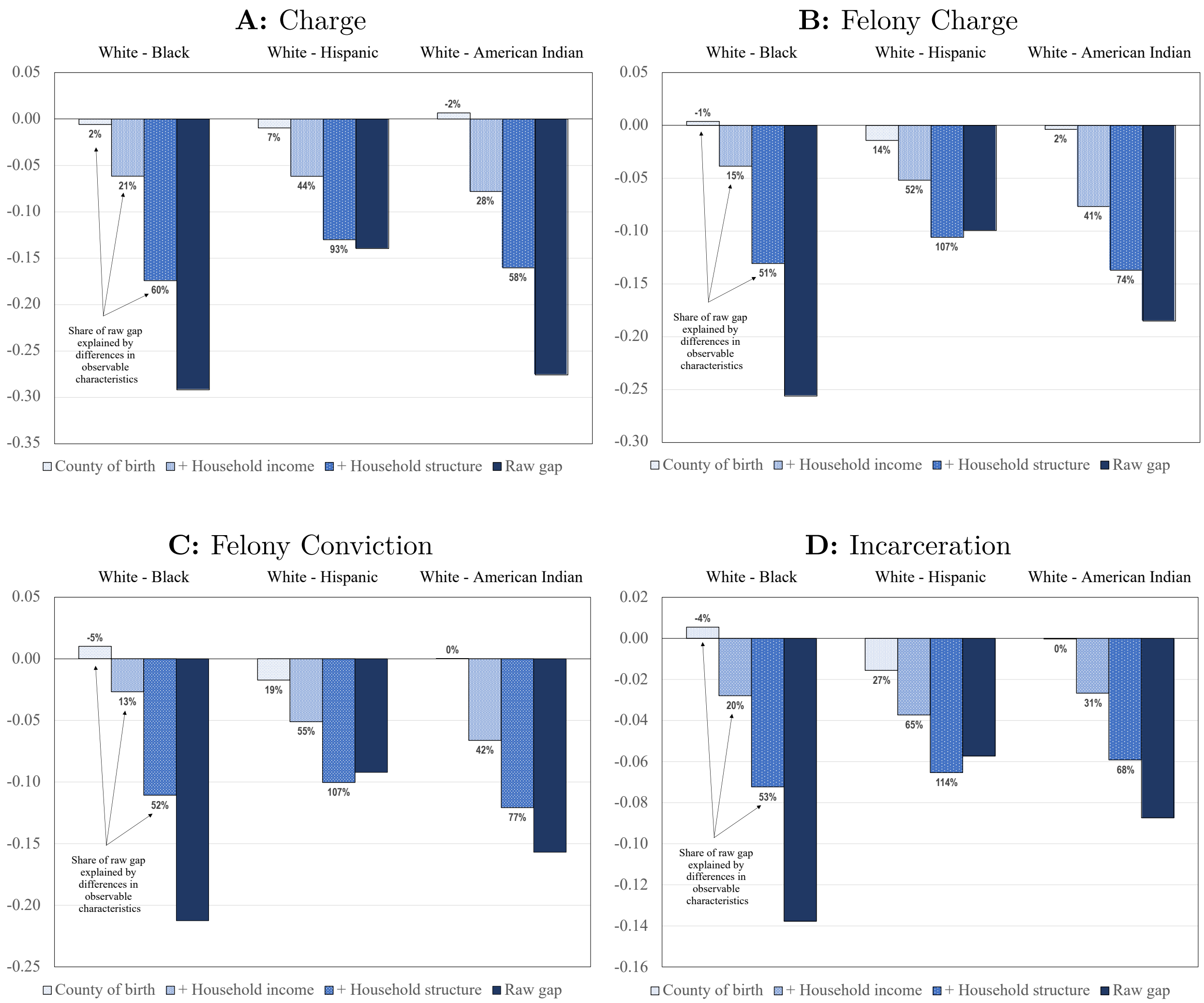
B: All biological parents



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, authorization numbers CBDRB-FY22-ERD002-001 and CBDRB-FY22-ERD002-003.

Figure 6: Oaxaca-Blinder decomposition of White-Minority gaps in intergenerational exposure



Source: Calculations are based on the Census Numident, CJARS, CJARS residence and relations crosswalk, and IRS Form 1040s.

Notes: The sample consists of children born in CJARS-covered states in 1999 and 2000 and remained covered until age 18. The gap in cumulative exposure by a potential caregiver is measured between minority and White children at the age of 18 for four types of criminal justice events: a criminal charge (Panel A), felony charge (Panel B), felony conviction (Panel C), or incarceration (Panel D). Estimated exposure is decomposed for each race using the county of birth, average Adjusted Gross Income (AGI) reported on the IRS Form 1040 in the year of the child's birth and next four years, and the number of caregiver links. The population-weighted average of the two decompositions (White coefficients applied to the minority population and minority coefficients applied to the White population) are reported for the three observed characteristics.

Figure 7: Correlations between intergenerational exposure and child outcomes

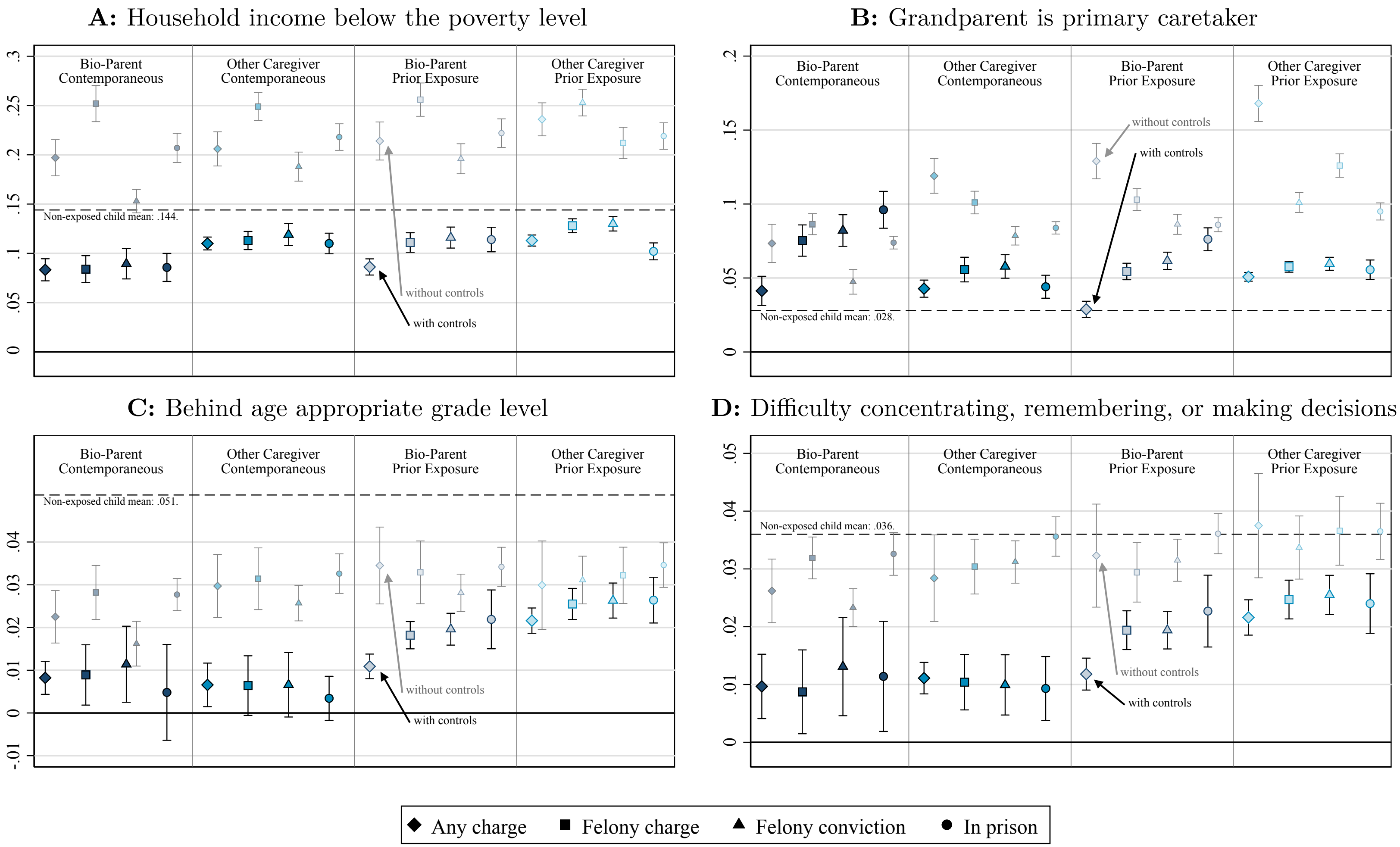
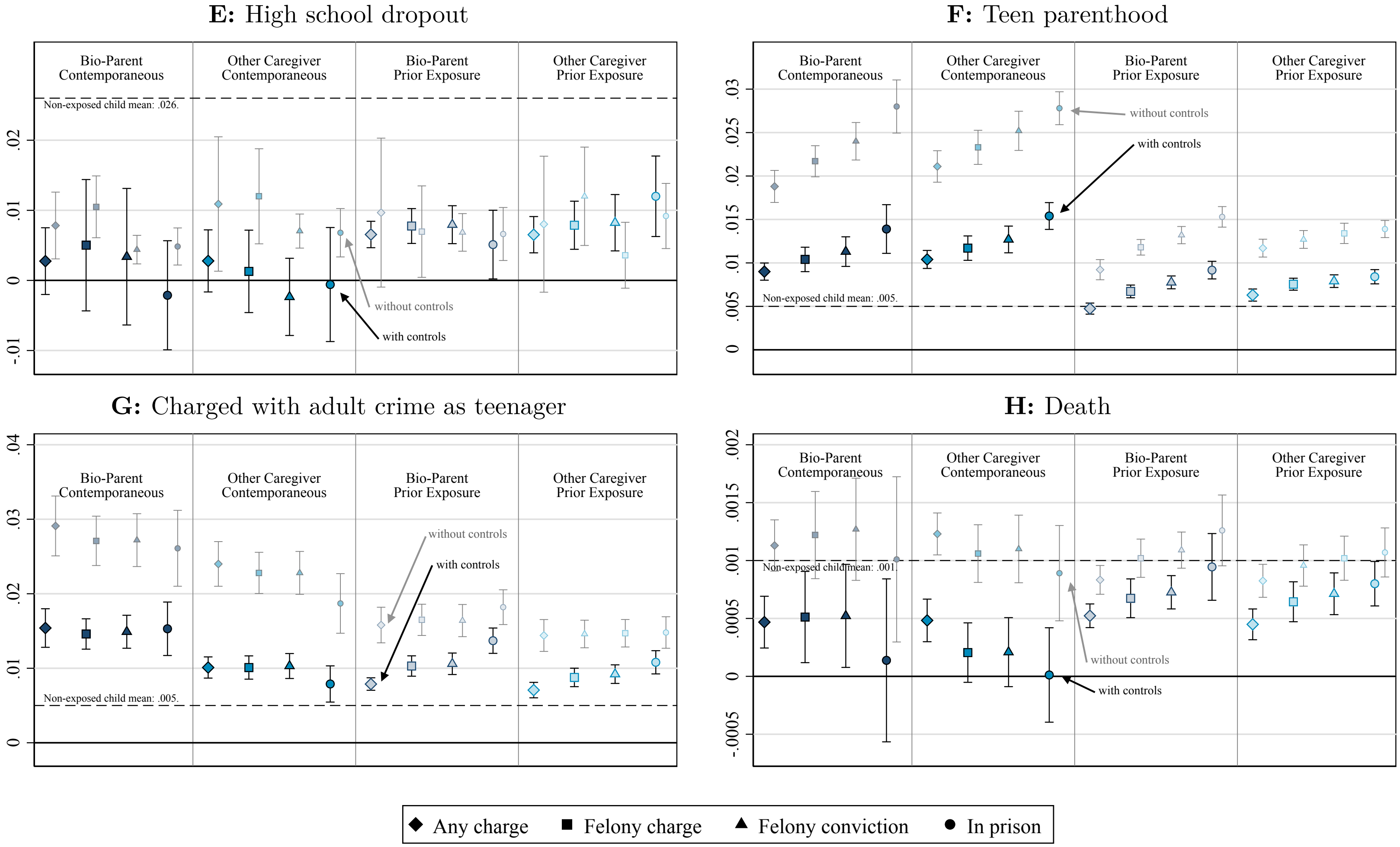


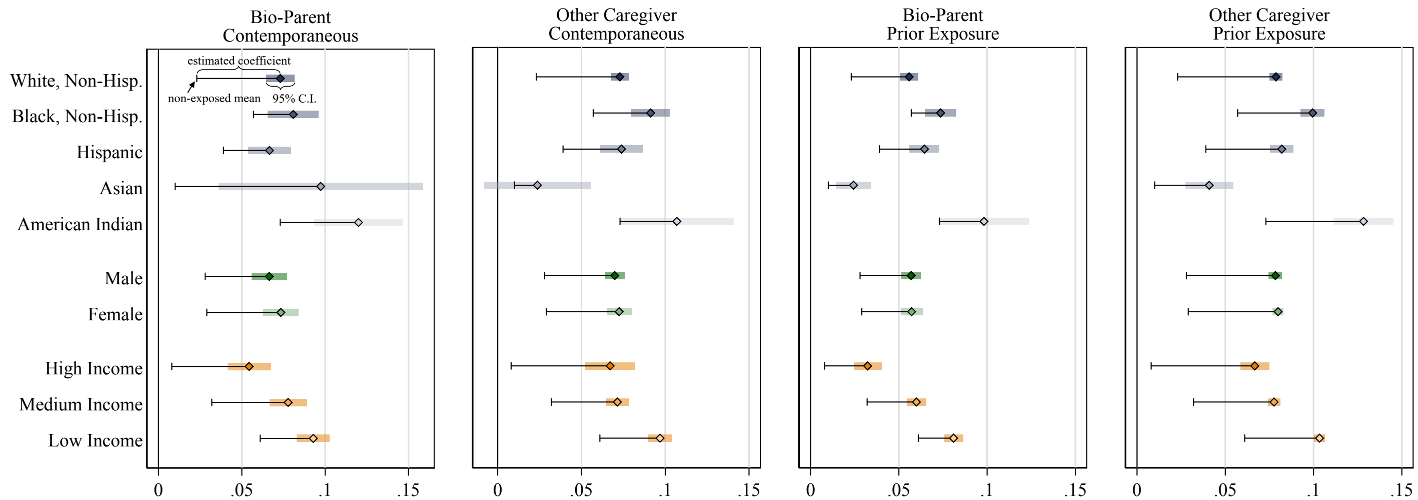
Figure 7: Correlations between intergenerational exposure and child outcomes (continued)



Source: Estimates are based on the 2005–2018 American Community Survey (outcomes), the Census Numident (year of birth, sex, mortality), the Census BestRace Files (race/ethnicity), CJARS (potential caregiver exposure and child adult charges) and the 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 X 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. For Panels A through E, 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 a charge is measured in the year of the survey, and prior exposure is measured from birth until the year prior to the survey response. For Panels F through H, the sample consists of children born in CJARS-covered states in 1999–2002, surviving until age 12. Contemporaneous exposure to any charge is defined for the teenage years (16–18) and prior exposure is from birth through age 15. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY22-ERD002-009.

Figure 8: Charge exposure and child development coefficient heterogeneity, by race, sex, and household income

A: Grandparent is primary caretaker



B: Difficulty concentrating, remembering, or making decisions

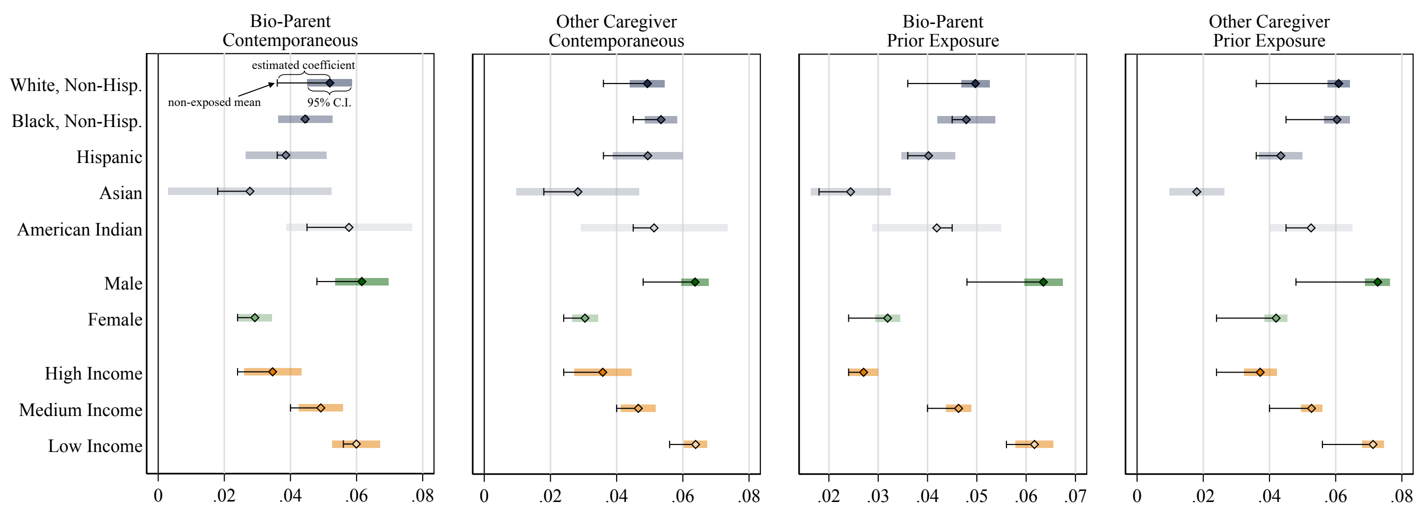
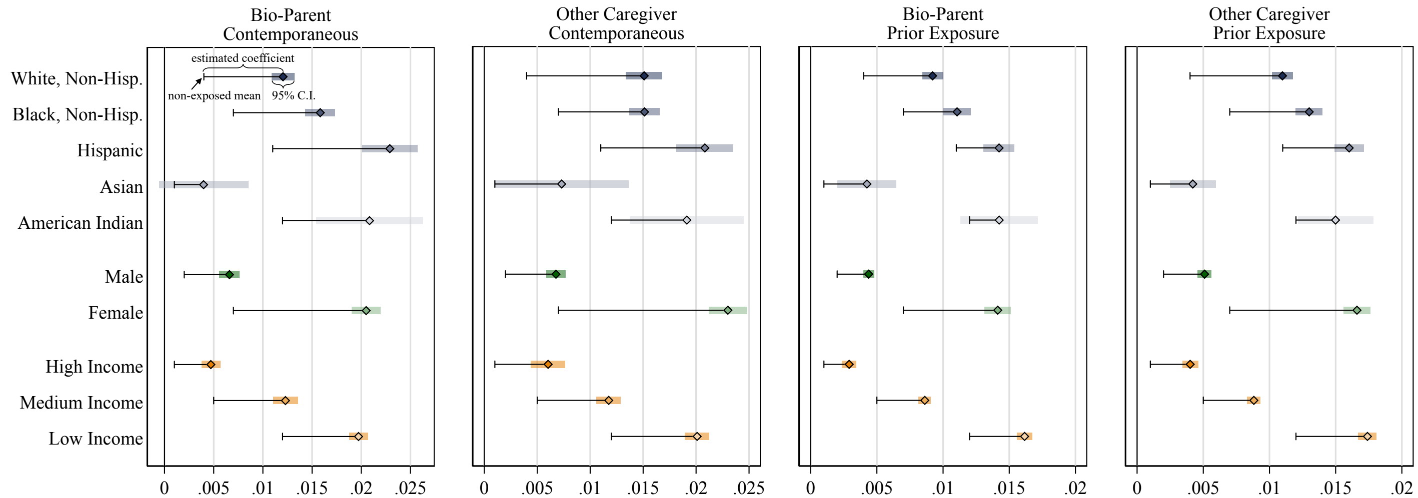
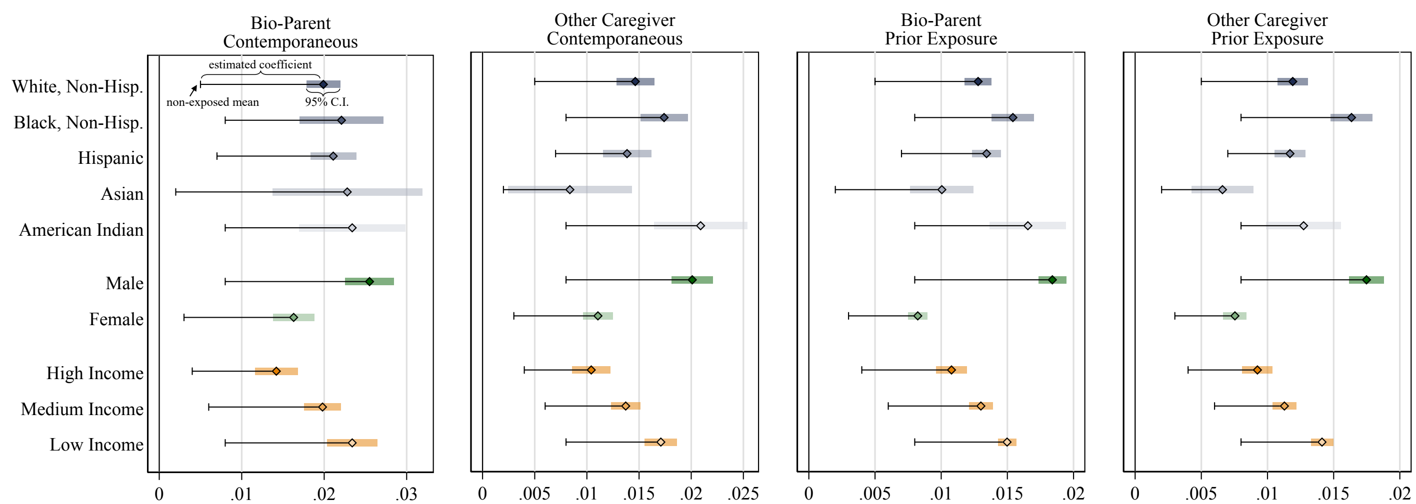


Figure 8: Charge exposure and child development coefficient heterogeneity, by race, sex, and household income (continued)

C: Teen parenthood



D: Charged with adult crime as teenager



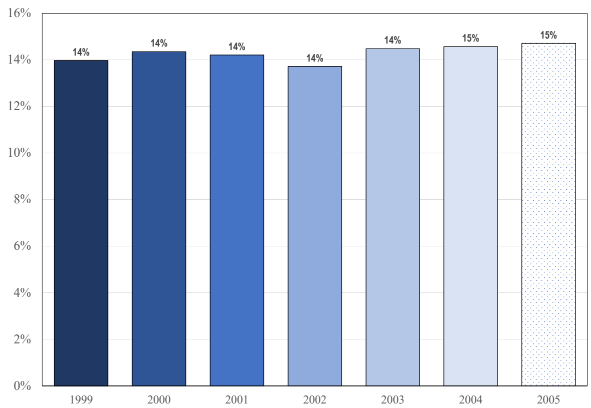
Source: Estimates are based on the 2005–2018 American Community Survey (outcomes), the Census Numident (year of birth, sex, mortality), the Census BestRace Files (race/ethnicity), CJARS (potential caregiver exposure and child adult charges) and the CJARS relationship crosswalk (identify potential caregivers and measure child fertility). Notes: Estimates and sample sizes have been rounded to preserve confidentiality. See Figure 7 notes for a description of outcomes, independent variables of interest, and the regression specifications with controls. Outcome means for non-exposed children by subgroup are depicted by the black vertical line with point estimates added to the mean, shown in diamonds, along with shaded 95% confidence intervals. All results were approved for release by the U.S. Census Bureau, authorization number CBDRB-FY22-ERD002-009.

Appendices

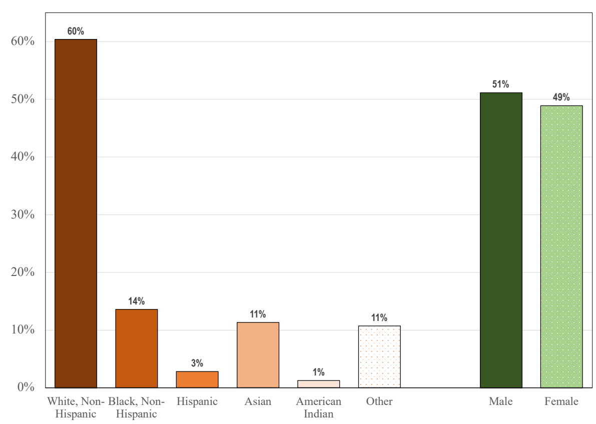
Appendix A Supplementary results

Figure A1: Composition of sample

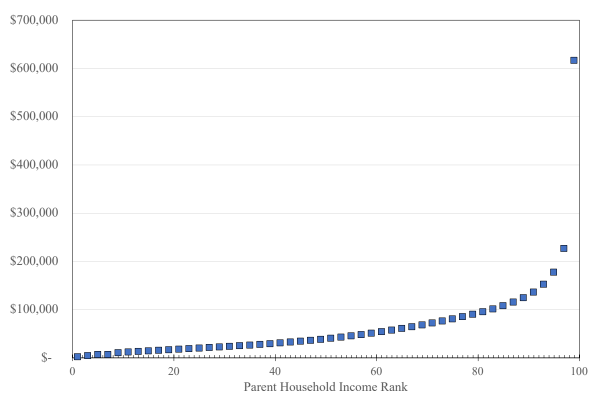
A: Birth year



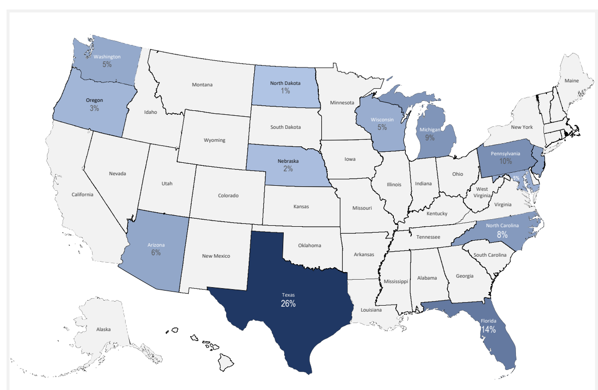
B: Child's race and sex



C: Average household AGI by percentile rank



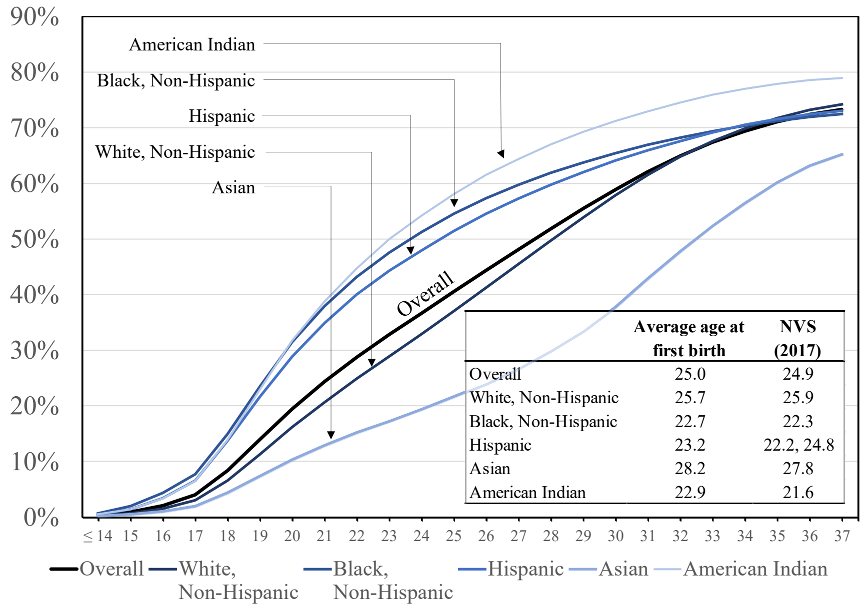
D: Place of birth



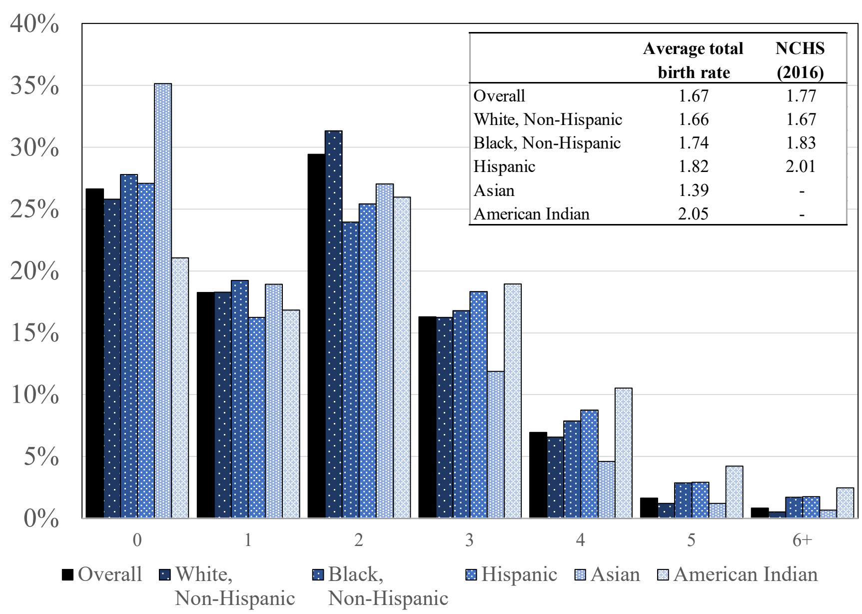
Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

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 D. Panel D depicts average AGI for children within percentile bins as rank-ordered within birth cohorts. All results were approved for release by the U.S. Census Bureau, authorization 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



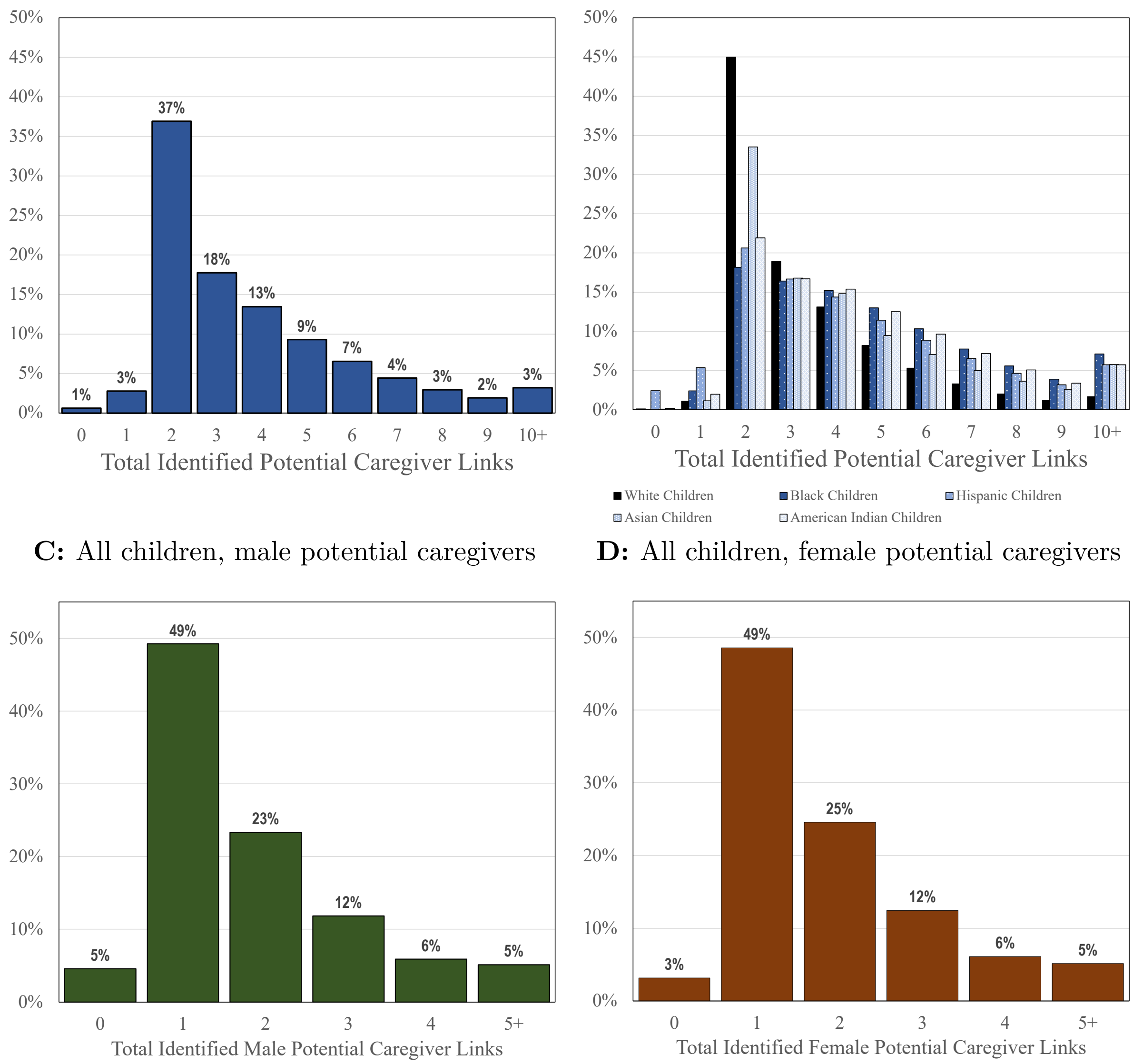
Source: Calculations are based on the Census Numident, the Census BestRace files, and the CJARS relationship crosswalk.

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, authorization 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

A: All children, all potential caregivers **B:** By child's race, all potential caregivers

C: All children, male potential caregivers **D:** All children, female potential caregivers

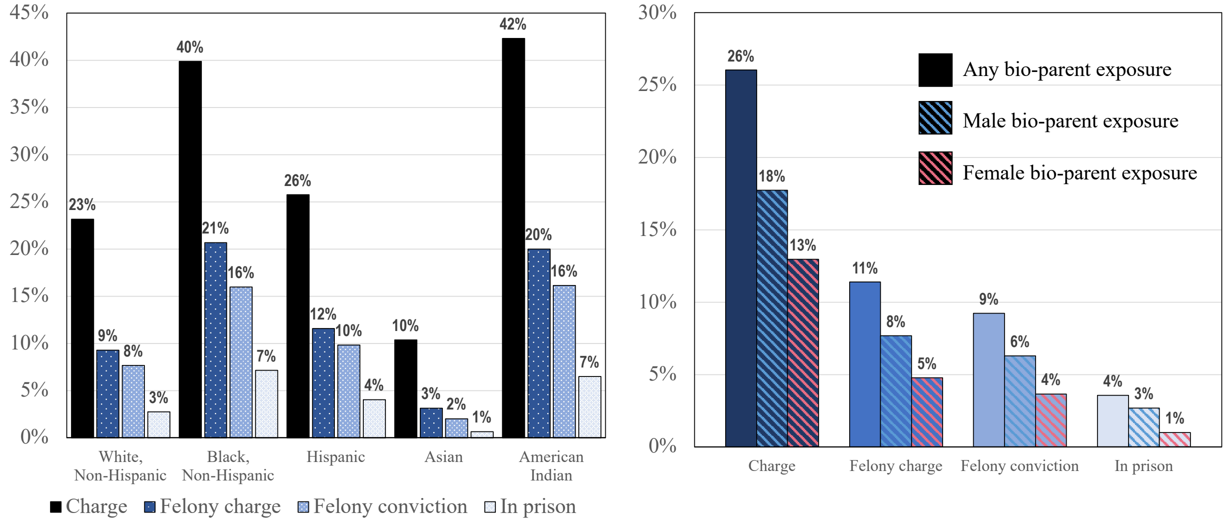


Source: Calculations are based on the Census Numident, the Census BestRace files, and the CJARS relationship crosswalk.

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: Heterogeneous cumulative exposure by biological parents

A: By child's race **B:** By biological parents' sex

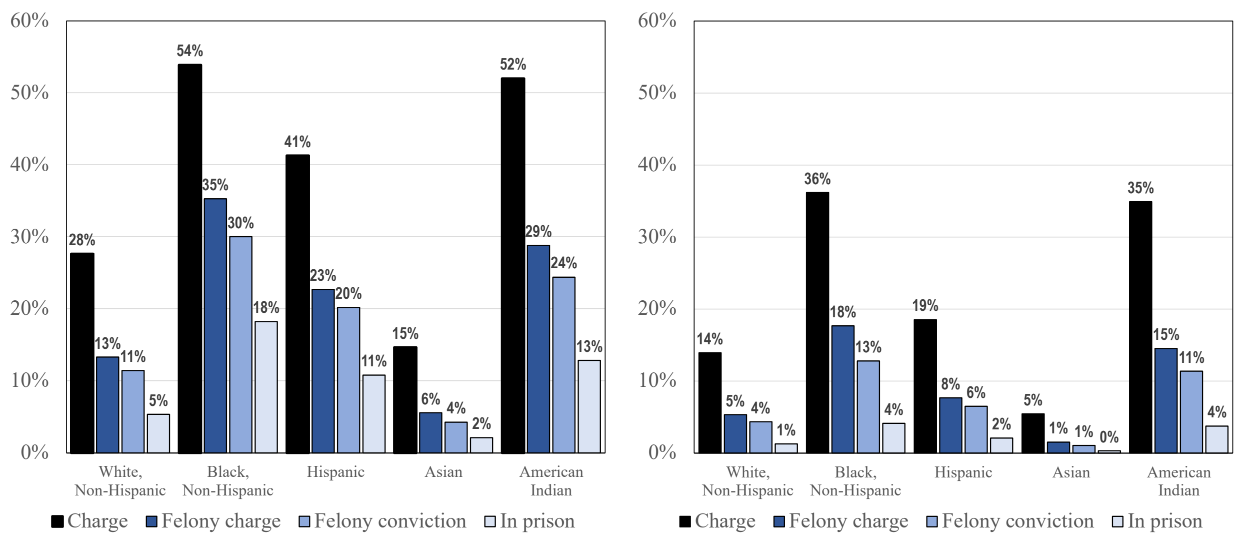


Source: Calculations are based on the Census Numident, the Census BestRace files, CJARS, and the CJARS relationship crosswalk.

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, authorization number CBDRB-FY22-ERD002-001.

Figure A5: Heterogeneous cumulative exposure by child race and adult sex

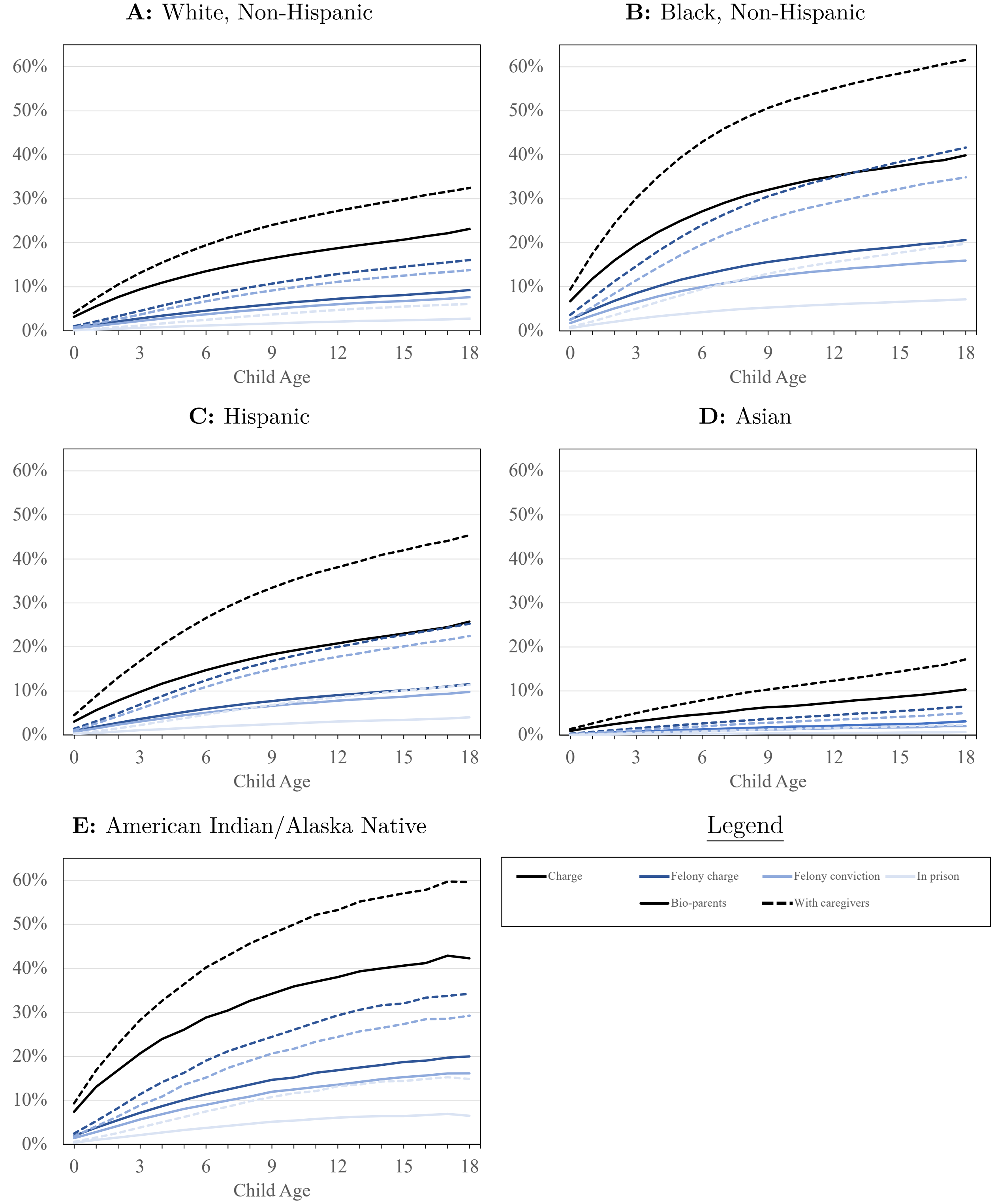
A: Male potential caregivers **B:** Female potential caregivers



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, authorization number CBDRB-FY22-ERD002-001.

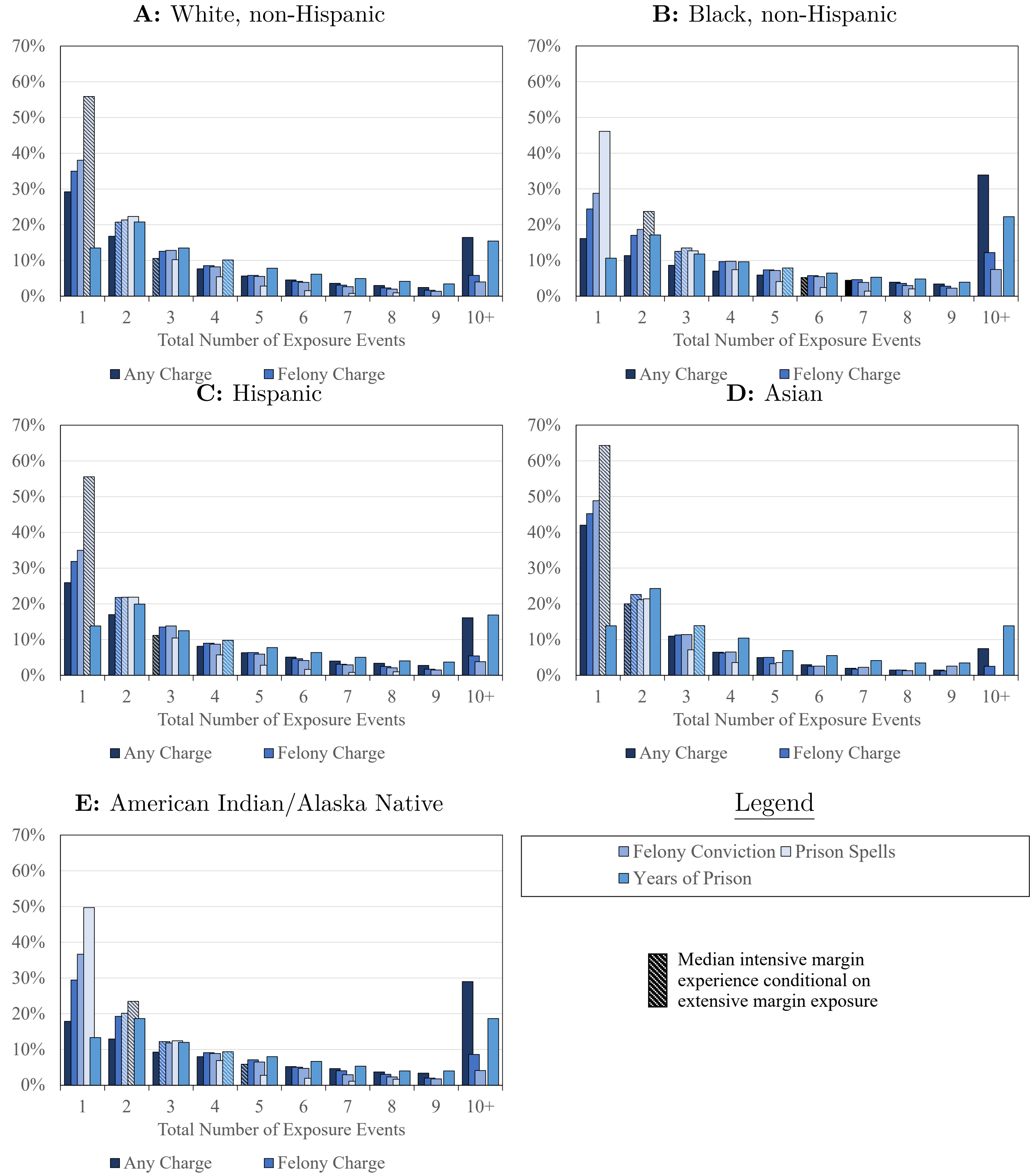
Figure A6: Cumulative exposure to the criminal justice system, by child's race



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

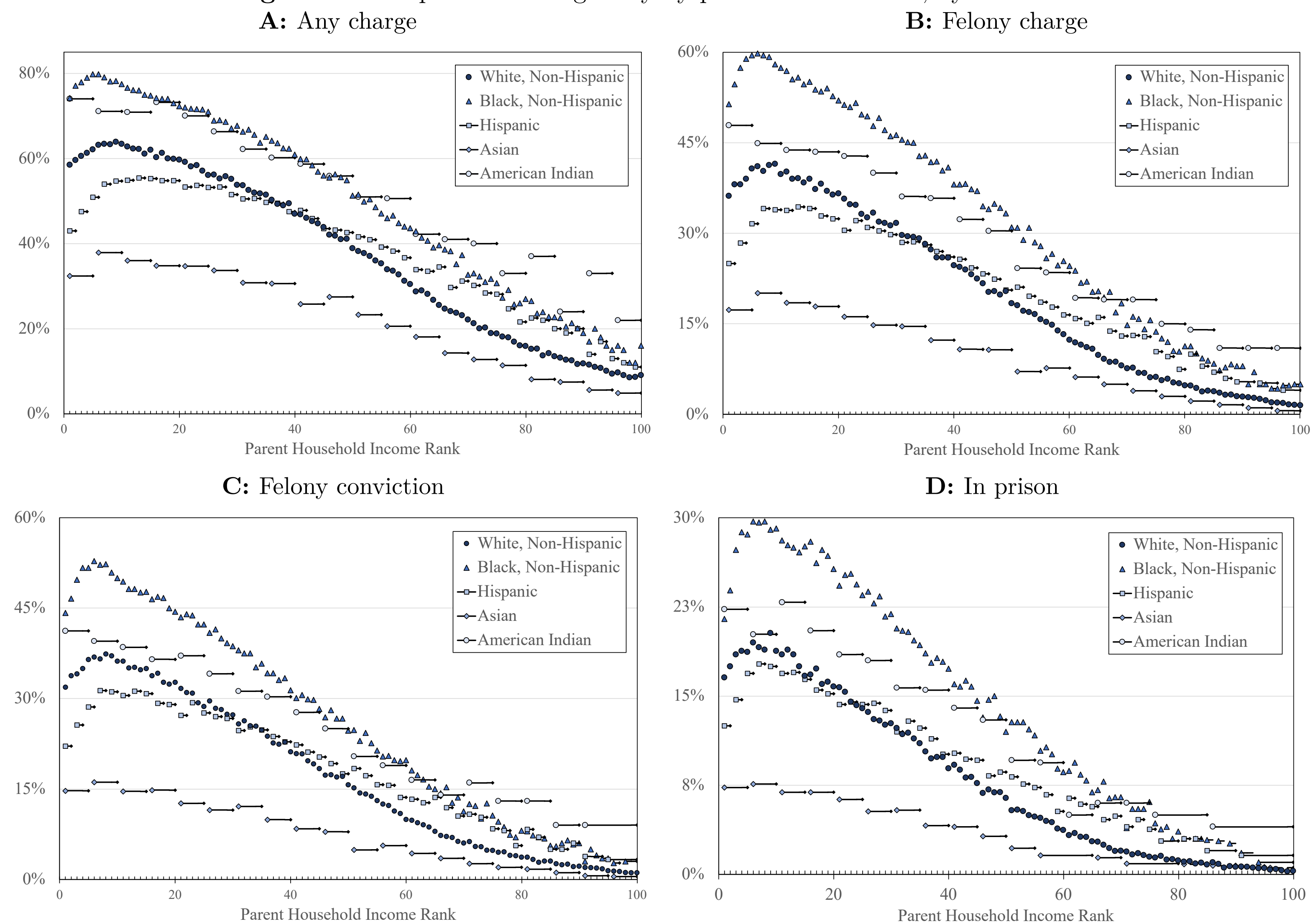
Notes: Estimates and sample sizes have been rounded to preserve confidentiality. The sample consists of individuals in the Census Numident 1999–2005 birth cohorts in CJARS-covered geographies from birth until X, where X represents years since birth (0–18) with the place of birth still covered or year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

Figure A7: 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, authorization numbers CBDRB-FY22-ERD002-003 and CBDRB-FY22-ERD002-009.

Figure A8: 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, authorization number CBDRB-FY22-ERD002-003.

Appendix 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.[46] The Census Numident is the "backbone" of the residence crosswalks, setting the population and identifying date and place of birth.[47] Address-level information is then harmonized for all subsequent years based on the 2000 and 2010 decennial censuses, American Community Survey (2001–2018),[48] IRS Form 1040 tax filings (1969, 1974, 1979, 1984, 1989, 1994, 1995, 1998–2018 tax years),[49,50] IRS Form 1040 electronic tax filings (2005, 2008–2012),[51] Department of Housing and Urban Development (HUD) program data (Longitudinal PIC/TRACS: 1995–2016, 2018; PIC: 2000–2014; TRACS: 2000–2014)[52] and county-level information from Medicare (2000–2017 EBD) and Medicaid (2000–2014 MSIS) enrollment databases,[53] Indian Health Service (IHS) from 1999–2017, and the MAF-ARF (2000–2018). Data are linked at the person-level using a Protected Identification Key (PIK) created through the Census Bureau's Person Identification Validation System (PVS).[54] 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, Amer-

[46]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, Sanders, and Stevenson (2021).

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

[48]There are small samples during the survey 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.

[49]Information varies by tax year and includes only the primary tax filer in 1969, primary and secondary filer in 1974–1989 and both filers and four dependents for the remaining tax years.

[50]IRS 1040s are based on tax years (TY). For example, the TY2009 1040s are filed in 2010 and thus provide an accurate address for individuals in the filing year, which is 2010. This was confirmed by comparing consistency with the 2010 Decennial Census.

[51]The electronic tax files allow information for up to 20 dependents.

[52]The longitudinal file is created by Census for research use combining information from the Public and Indian Housing Information Center (PIC) and Tenant Rental Assistance Certification system (TRACS).

[53]CMS MSIS only provides county-level geographic information.

[54]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).

ican 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 assigned unique address identification numbers. Instead, examples of group quarters include dormitory facilities, assisted living facilities, nursing homes, and prisons. 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),[55,56,57] IRS Form 1040 electronic tax filings (2005, 2008–2012),[58] 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).[59] 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, Sanders, and Stevenson 2021; B. Bond et al. 2014). We confirm that 93% of the biological relationships identified by our crosswalk are also observed in the

[55] Information varies by tax year and includes only the primary tax filer in 1969, primary and secondary filer in 1974–1989 and both filers and four dependents for the remaining tax years.

[56] Again, IRS 1040s are based on tax years (TY). For example, the TY2009 1040s are filed in 2010 and thus provide an accurate address for individuals in the filing year, which is 2010. Relations are also established for the year 2010 when they are observed coresiding at a specific location to match the residence crosswalks, although officially the relation existed in 2009.

[57] Individuals in the 1040s receive a PIK deterministically from their SSN or ITIN. However, the address information used to determine the associated MAFID is probabilistic. Thus, we are able to make some relational pairs using filing information even if we can not match them to a specific MAFID in the residence crosswalk.

[58] The electronic tax files allow information for up to 20 dependents.

[59] 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.

CHCK file. Additionally, 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:

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

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 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.[60,61] Second, the American Community Survey between 2001–2007 and 2010 Decennial Census uses broader relationship definitions.[62] Finally, parental relations that are established only in the tax 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.[63]

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.

[60]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.

[61]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.

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

[63]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.

in 1981, as measured by the Census Numident.[64,65] 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 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 1A). 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.[66]

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 (B. Bond et al. 2014).

[64]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.

[65]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.

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

Figure 1B 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.[67] Unclassified caregivers, which occur when we observe an adult-child link resulting of dependency claims in IRS tax records without any other information to pin down the nature of their relationship, are more likely in intergenerational households,[68] and among biological parents that are left off of birth records (as proxied by the CHCK file). 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.[69]

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.

[67] 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.

[68] 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.

[69] 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.

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.

Figure B1: Sequential process to establish relations beyond cohabitation

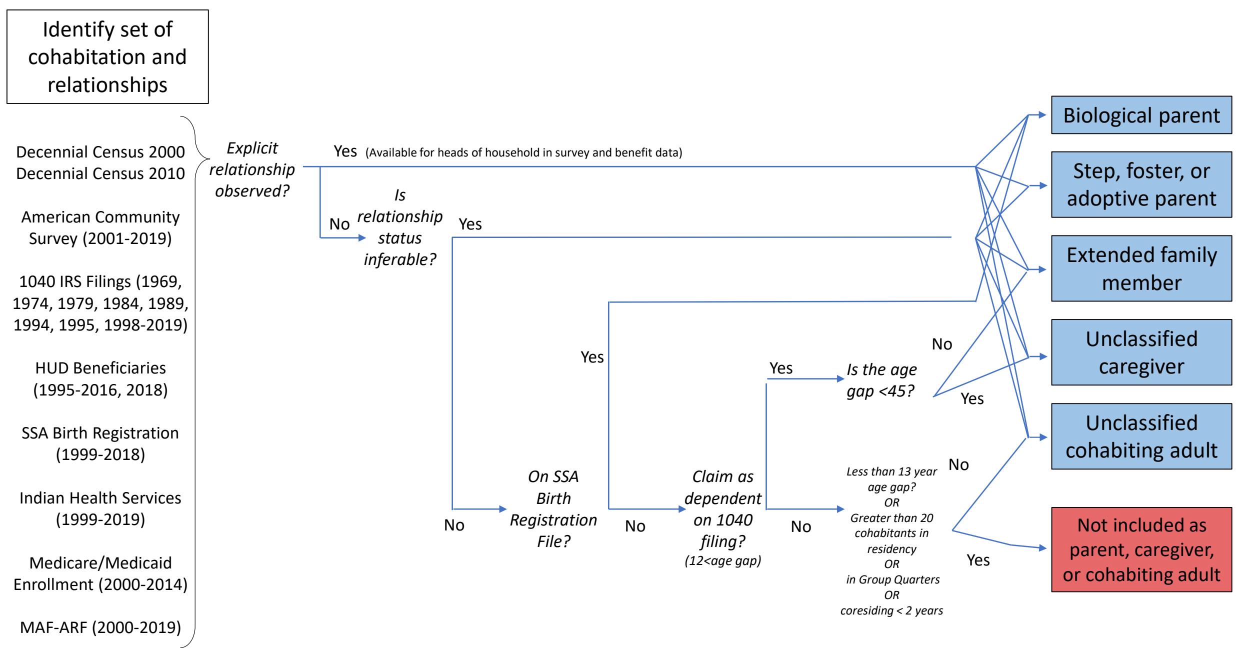


Figure B2: Construction of residential and relations crosswalks

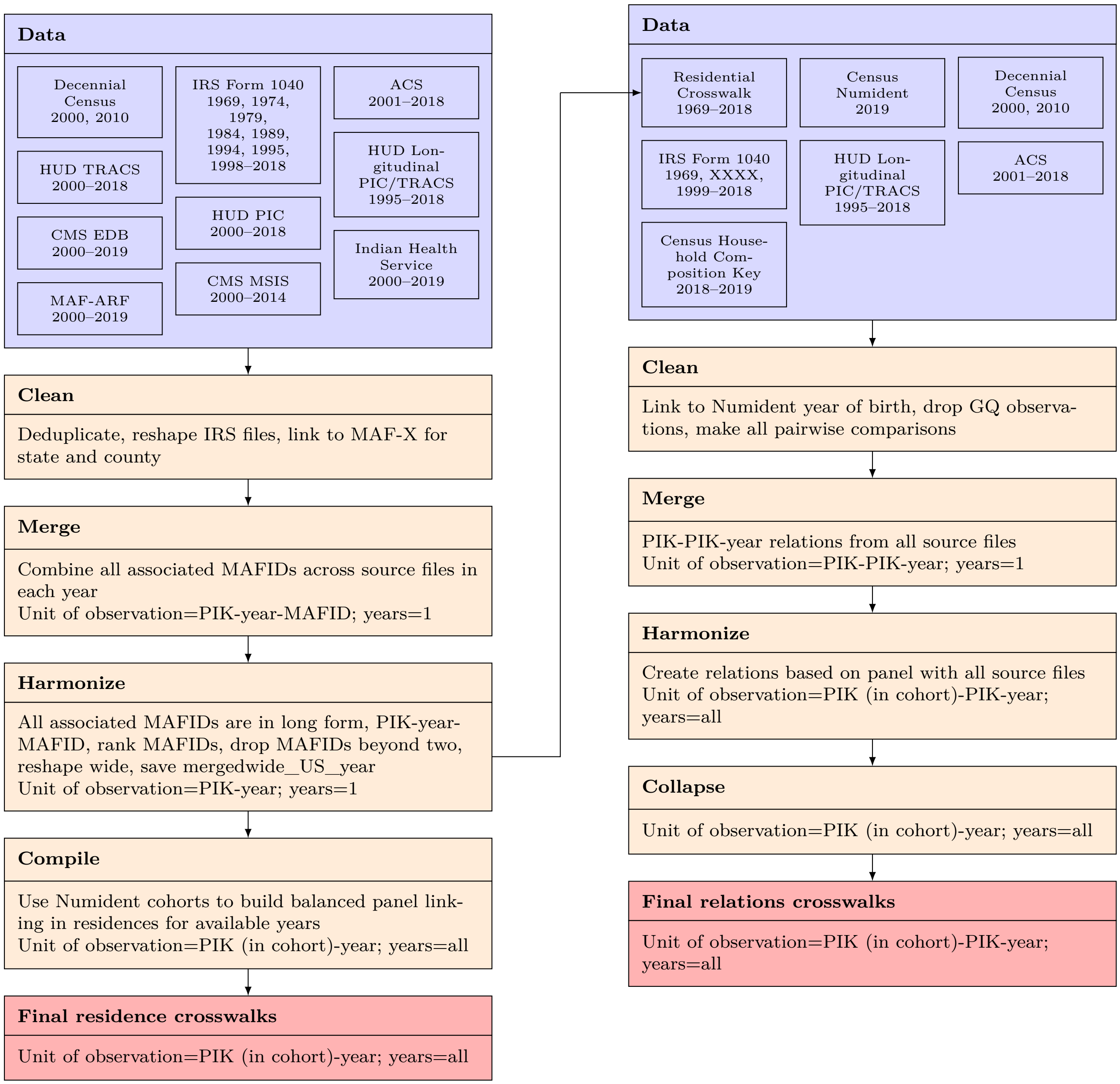
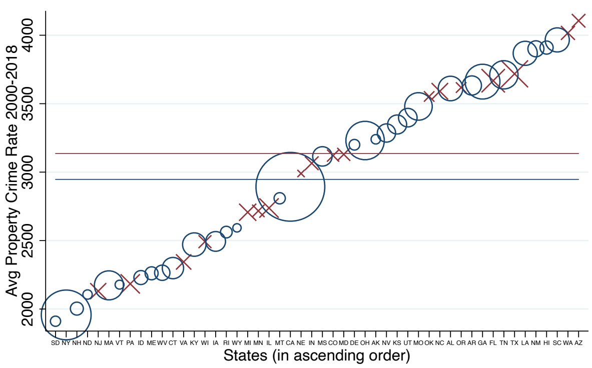
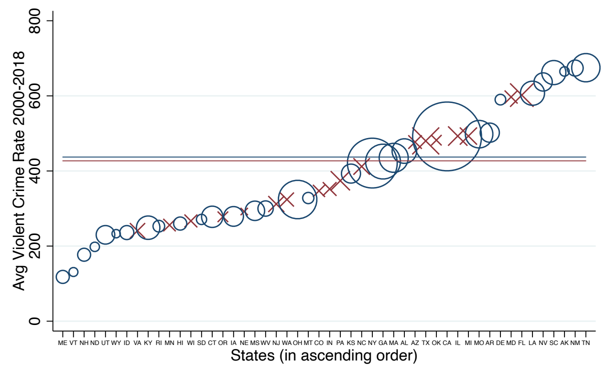


Figure B3: State comparisons, crime and criminal justice outcomes

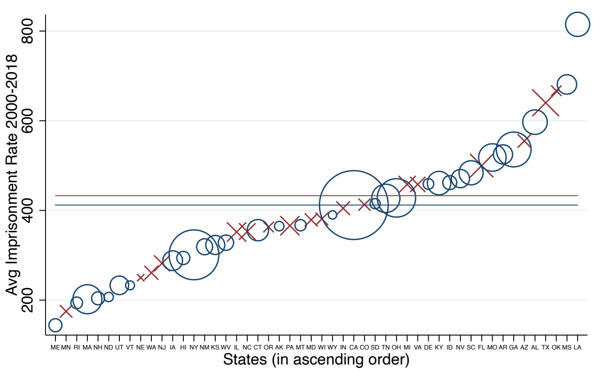
A: Property Crime Rates (UCR)



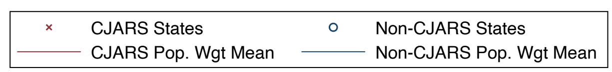
B: Violent Crime Rates (UCR)



C: Incarceration Rates (BJS)



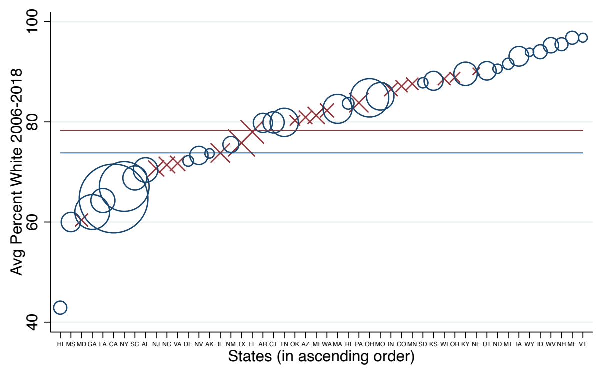
Legend



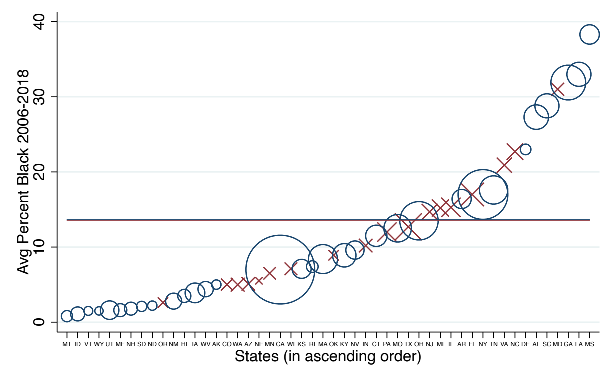
Notes: Data come from the Federal Bureau of Investigation's Uniform Crime Reporting (UCR) program and the Bureau of Justice Statistics National Prisoner Statistics program. The rates per 100,000 residents have been averaged for each state over the period 2000–2018. Marker sizes are proportional to each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

Figure B4: State comparisons, socioeconomic outcomes

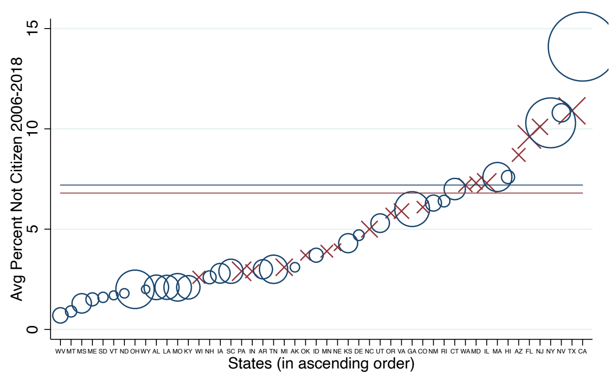
A: Percent Population White



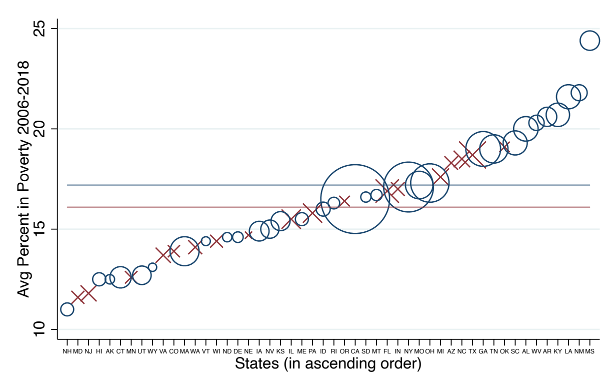
B: Percent Population Black



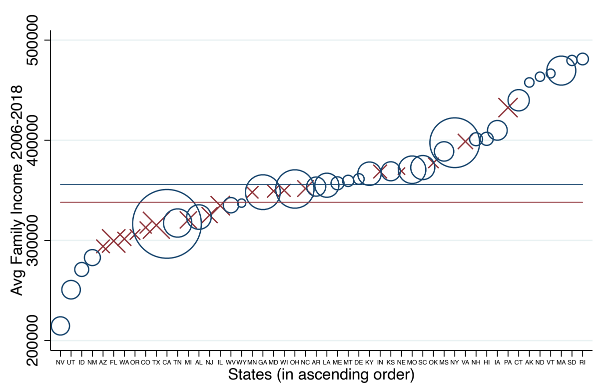
C: Percent Not A Citizen



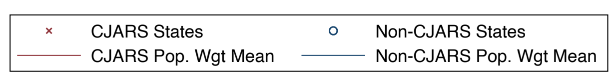
D: Percent In Poverty



E: Family Total Income



Legend



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 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.

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. (2022).