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The Role of Single Motherhood in America's High Child Poverty

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THE ROLE OF SINGLE MOTHERHOOD IN AMERICA'S HIGH CHILD POVERTY

ABSTRACT

Many claim a high prevalence of single motherhood plays a significant role in America's high child poverty. Using the Luxembourg Income Study, we compare the "prevalences and penalties" for child poverty across 30 rich democracies and over-time within the U.S. 1979-2019. Several descriptive patterns contradict the importance of single motherhood. The U.S. prevalence of single motherhood is cross-nationally moderate and typical, and historically stable. Also, child poverty and the prevalence of single motherhood have trended in opposite directions in recent decades in the U.S. More important than the prevalence of single motherhood, the U.S. stands out for having the highest penalty across 30 rich democracies. Counterfactual simulations demonstrate that reducing single motherhood would not substantially reduce child poverty. Even if there was zero single motherhood: (a) the U.S. would not change from having the fourth highest child poverty rate; (b) the 41-year trend in child poverty would be very similar; and (c) the extreme racial inequalities in child poverty would not decline. Rather than the prevalence of single motherhood, the high penalty for single motherhood and extremely high Black and Latino child poverty rates – that exist regardless of single motherhood – are far more important to America's high child poverty.

Many have long argued that single motherhood is one of the most important causes of poverty (see Cohen 2018; Fremstad and Boteach 2015; O'Connor 2001; Madrick 2020). Indeed, an enduring view has been that the high prevalence of single motherhood is a major reason the U.S. has high child poverty. Moynihan's (1965) report "On the Negro Family" declares single motherhood is "the fundamental problem" driving Black poverty in the U.S. Bane and Ellwood (1994:55) claim, "Welfare use begins because single-parent families are formed. If we could prevent the formation of single-parent families, we could largely eliminate the need for Aid to Families with Dependent Children." Amato and Maynard (2007: 118) conclude, "[A] major cause of the rise of child poverty in the United States during the second half of the twentieth century is the decline of married couple households."

As a result, many contend that reductions in single motherhood would result in substantially lower child poverty (Amato and Maynard 2007; Garfinkel and McLanahan 1986; Jencks 1992; Thomas and Sawhill 2005; Sawhill 2014). Ellwood and Jencks (2004: 4) argue, "Those whose primary goal is to reduce child poverty should mainly worry about the increased proportion of children living with only one adult." Such claims have been common by public intellectuals (Hymowitz 2018; Samuelson 2018; Wilcox and Sawhill 2018) and prominent scholars. For example, the first recommendation of the bipartisan 2015 AEI-Brookings "Consensus Plan for Reducing Poverty and Restoring the American Dream" is to "promote a new cultural norm surrounding parenthood and marriage."[1] A 2022 AEI-Brookings "Consensus Report" advocates, "marriage is the best path to favorable outcomes. . .marriage offers the most reliable way" (p.22) and, "Child poverty would be markedly reduced if the marriage rate was the

[1] The AEI-Brookings reports were explicitly bipartisan and co-authored by eminent social scientists, including Aber, Danziger, Deming, Ellwood, Gennetian, Haidt, Holzer, Mincy, Simon, Sullivan, Waldfogel, and Whitmore Schanzenbach.

same as it was in 1970" (p.28). Such claims were also mobilized against the Biden administration's expanded child tax credit (Rubio 2021; Winship 2021).

These claims build on extensive literatures on single motherhood and child poverty. Despite these contributions, we propose that the role of single motherhood warrants greater scrutiny. In turn, this study reexamines the role single motherhood plays in America's high child poverty. We apply the "prevalences and penalties" (PP) framework, which decomposes the major risks for poverty in terms of the share of the population with a risk (prevalences) and the increased probability of poverty associated with a risk (penalties) (Brady et al. 2017). Using the Luxembourg Income Study (LIS), we compare the prevalences and penalties for child poverty across 30 rich democracies and within the U.S. over four decades, 1979-2019. We then conduct counterfactual simulations to assess how much substantial and dramatic reductions in – and even the complete elimination of – single motherhood could reduce U.S. child poverty in 2018. Compared to prior PP studies, we uniquely concentrate exclusively on single motherhood and child poverty in the U.S. We explain below this presents a particularly strong challenge for the PP framework.

PRIOR RESEARCH

For several decades, demographic trends have raised concerns about a link between marriage, childbearing, and child poverty. These trends begin with a "fundamental transformation of the American family since the 1960s," including a marked decline in marriage and an increase in non-marital births (Cherlin 2010: 146). Non-marital births doubled from the late 1970s through the early 1990s and rose again in the early 2000s (Schneider and Gemmill 2016). Meanwhile, official child poverty rose sharply in the 1980s, and became more concentrated among young, unmarried mothers and their children (Bianchi 1999). This "new American dilemma" was particularly troubling because nearly half of all single mother families were living in poverty, and these children remained poor more than a third of their childhood (Garfinkel and McLanahan 1986).

An extensive literature studies the relationship between single motherhood and child and family poverty (Amato and Maynard 2007; Ananat and Michaels 2008; Baker 2022; Cancian and Reed 2009; Eggebeen and Lichter 1991; Ellwood and Jencks 2004; England and Edin 2010; Garfinkel and McLanahan 1986; Hogendoorn et al. 2020; Lichter et al 2005; Lichter et al. 2003; McKeever and Wolfinger 2011; Musick and Mare 2004; Sawhill 2014). Accordingly, Brady and Burroway (2012:739) conclude, "[S]ingle motherhood may be the most well-studied correlate of poverty." Indeed, some claim single motherhood has a causal effect on child poverty (Amato and Maynard 2007; McLanahan 1985; McLanahan and Percheski 2008; Thomas and Sawhill 2002). This has motivated many to ask why single mother households (HHs) are formed and what explains the prevalence of single motherhood (AEI-Brookings 2015, 2022; Amato and Maynard 2007; Ellwood and Jencks 2004; England and Edin 2010).

Various analyses decompose how much trends in child poverty are attributable to changes in family structure. Such studies often simulate how changes in family structure would substantially reduce child poverty (Sigle-Rushton and McLanahan 2002). For instance, Eggebeen and Lichter (1991) use direct standardization to assess how changes in the share of children across different family types increased child poverty. They find that if family structure had remained at 1960 levels, child poverty rates would have been one-third less in 1988. Lerman (1996) simulates matching unmarried men and women in the same marriage pool by race, age, and education, and concludes that practically all of the increase in child poverty 1971-1989 is attributable to changes in family structure. Thomas and Sawhill (2002) extend Lerman's approach with a broader definition of income. They simulate marriage by randomly assigning single mothers to unrelated men with the same race, age, and education anywhere in the U.S. Their simulations reduce overall child poverty by 3.5 percentage points and reduce poverty for the single mother families simulated to be married by two-thirds.

The link between single motherhood and child poverty has been especially pronounced among Black families, who comprise a disproportionate share of non-marital births, single mothers, and poor children (Baker 2022; Baker and O'Connell 2022; Bianchi 1999; Ellwood and Jencks 2004; Williams and Baker 2021). In turn, single motherhood is often emphasized as critical to why there are large racial inequalities in child poverty (Bane and Ellwood 1994; Bloome 2014; Lichter et al. 2005). Eggebeen and Lichter (1991) find that higher rates of Black single motherhood since 1960 exacerbated Black-White disparities in child poverty. More recently, Iceland (2019) concludes family structure is the most important factor driving Black-White inequalities in poverty.

THE PREVALENCES AND PENALTIES FRAMEWORK

Attention to single motherhood reflects a longstanding interest in the risks for poverty (Brady 2023; Madrick 2020; O'Connor 2001; Rank 2005). Risks are the non-ascriptive labor market and family characteristics more common among the poor than non-poor. Single motherhood, young headship, joblessness, and low education have been shown to be the four major risks of poverty (Brady et al. 2017).

Building explicitly on classic demographic decomposition techniques (e.g., Kitagawa 1955), Brady and colleagues (2017) developed the PP framework to describe and assess how much risks explain poverty (for applications, see Baker 2022; Baker et al. 2022; Laird et al. 2018; Rothwell et al. 2019; Rothwell and McEwen 2018; Thiede et al. 2021; Williams and Baker 2021; Zagel et al. 2021). The PP framework draws a critical distinction between prevalences and penalties. The prevalences are the share of the population with a given risk. The penalties are the greater probabilities of poverty associated with a given risk.

While the prevalence of single motherhood has been the principal focus of prior research, the PP framework clarifies that the risks of poverty can also be addressed by reducing penalties (Brady 2023; Baker 2022). For overall working-aged poverty, there is more cross-national variation in penalties than prevalences, reducing penalties would lower poverty more than reducing prevalences, and the U.S. has high poverty because it has high penalties despite below average prevalences (Brady et al. 2017). For single motherhood in particular, the U.S. has an unusually high penalty (Brady and Burroway 2012; Maldonado and Nieuwenhuis 2015; Misra et al. 2012). By contrast, the single motherhood penalty is substantively small and statistically insignificant in most other rich democracies (Brady et al. 2017). Thus, reducing the U.S. penalty for single motherhood – rather than prevalence – could more effectively reduce child poverty (Rothwell and McEwen 2018).

The PP approach raises at least three additional questions about prior research. First, prior research tends to focus on the raw unconditional differences in child poverty between married and single mother HHs. These raw differences underlie the aforementioned simulations (Eggebeen and Lichter 1991; Lermer 1996; Thomas and Sawhill 2002). However, single motherhood is confounded with other risks and characteristics (Zagel et al. 2021). Single mothers are disadvantaged in terms of education, employment, and age relative to couples (Brand et al. 2019; Cohen 2018; Cross 2019; Ellwood and Jencks 2004; Harkonen 2018;

Hogendoorn et al. 2020; Rodriguez Sanchez 2022). Indeed, McLanahan's "diverging destinies" thesis and the assortative mating literature (e.g. Xie et al. 2015) contend single mothers are adversely selected such that single motherhood exacerbates preexisting disadvantages. As a result, raw unconditional differences in child poverty between married couples and single mothers likely exaggerate the impact of single motherhood (Baker et al. 2022). To correctly estimate how much lower prevalences of single motherhood would reduce child poverty, it is essential to estimate the penalty for child poverty conditional on other risks and predictors of poverty (Brady et al. 2017; Zagel et al. 2021).[2]

Second, prior research presumes the U.S. has a high and increasing prevalence of single motherhood. By contrast, the PP framework scrutinizes whether the U.S. prevalence of single motherhood is high compared to other rich democracies. Brady and colleagues (2017) demonstrate single mother HHs are actually only a modest and fairly stable share of people in working-aged HHs in the U.S. As a result, lower prevalences of single motherhood should not result in substantially lower overall working-aged poverty. This point builds upon a handful of prior comparative studies questioning the role of family structure for cross-national variation in child poverty (Chen and Corak 2008; Gornick and Jäntti 2012; Heuveline and Weinshenker 2008).[3] This point also builds on studies scrutinizing the role of the prevalence of single motherhood in racial inequalities in poverty (Baker et al. 2022; Williams and Baker 2021).

[2] If other risks are not just confounded but actually mediate between single motherhood and poverty, one could block the causal pathway between single motherhood and poverty. However, we explain below that this concern should not discourage estimating penalties as conditional (Brady et al. 2021). Below, we estimate both conditional and unconditional single motherhood penalties with alternative model specifications and assumptions.
[3] While this analysis explicitly builds upon prior comparative studies, for brevity, we enumerate a variety of detailed ways we advance beyond such studies in Appendix X.

Third, prior research tends to lack comparisons of the magnitude of the single mother penalty against the penalty for other risks. If other risks have much larger penalties than single motherhood, reducing the prevalence of single motherhood will be less effective than reducing other risks (Laird et al. 2005). Among working-aged-headed HHs, Brady and colleagues (2017) show single motherhood is the least important of the four major risks. Others show the association between single motherhood and child poverty has declined since the 1980s (Baker 2015; Musick and Mare 2004). By contrast, employment has become more important than single motherhood for child poverty (Baker 2015; Lichter et al. 2005) and racial inequality in poverty (Baker et al. 2022; Thiede et al. 2017).

Despite these points, American child poverty presents a particularly strong challenge for the PP framework. While Brady and colleagues analyze overall working-aged poverty, single motherhood is far more likely to drive child poverty specifically (Hymowitz 2018; Samuelson 2018; Wilcox and Sawhill 2018). Analyses of overall poverty might dilute and understate the effects of single motherhood. Indeed, no one argues that single motherhood matters to poverty among childless adults. The prevalence of single motherhood is also far higher among American children than among working-age HHs. It is plausible that child poverty depends more on risk prevalences than overall poverty, partly because there could be less variation in the penalties for child poverty. Even though the U.S. has a comparatively weak welfare state, social policies targeted at children could reduce penalties for children (e.g. the Earned Income and Child Tax Credits). If so, penalties could be less important for child versus adult poverty. In turn, it may be more effective to reduce prevalences. Therefore, while cross-national comparisons are informative, the distinctiveness of the case of recent U.S. history requires singular scrutiny.

METHODS

We use the Luxembourg Income Study (LIS), an archive of harmonized individual-level nationally representative datasets. Advantageously, the LIS has high quality and standardized measures of income and other characteristics. We use a recent pre-COVID wave of LIS data for 30 rich democracies. We also analyze annual waves of LIS data for the U.S., drawn from the Current Population Survey: 1979-2019.

The sample is children under age 18 in HHs. The unit of the analysis is the individual child. Sample sizes vary across countries but are large enough to reasonably estimate prevalences and penalties (e.g. U.S. samples vary 36,425-67,930).

The LIS is publicly available. For transparency, we provide our LIS code in the Supplementary File. This code enables readers to replicate our analyses immediately.

Poverty

We define poverty as relative to the prevailing standards of living and consumption within each country-year (Fremstad 2020; Gornick and Jäntti 2012; Rainwater and Smeeding 2004; Smeeding 2016). Poverty is a shortage of resources compared to needs (Smeeding 2016), and both resources and needs are defined in the context of a time and place. Following the overwhelming majority of international poverty research (e.g., Baker 2015; Brady 2023; Brady and Burroway 2012; Brady et al. 2017; Fremstad 2020; Gornick and Jäntti 2012; Heuveline and Weinshenker 2008; Misra et al. 2012; Rainwater and Smeeding 2004; Rothwell and McEwen 2018; Smeeding 2016), we operationalize *poverty* as those residing in HHs with less than 50% of the median equivalized disposable HH income (reference=not poor). We measure income with the LIS's high-quality measure of disposable HH income (DHI) that incorporates taxes and transfers (Rainwater and Smeeding 2004). We equivalize income by dividing by the square root of the number of HH members. The poverty thresholds are established with population weights in the entire (not just child) sample.

Unlike prior research, we avoid the official U.S. measure of poverty (OPM) because it has large validity and reliability problems (Baker et al. 2022; Brady 2023; Fremstad 2020; Madrick 2020; O'Connor 2001; Rainwater and Smeeding 2004; Smeeding 2016). For brevity here, Appendix I: (a) justifies relative poverty measurement, (b) details the OPM's problems, and (c) provides alternative analyses with both a "quasi-OPM" and anchored measure.

Prevalences and Penalties

We use the same measures as prior PP studies (Baker 2022; Brady et al. 2017; Laird et al. 2018; Rothwell et al. 2019; Thiede et al. 2021; Zagel et al. 2021). Prevalences are the shares of the population with each of the four risks. *Single motherhood* is defined as those in a HH led by an unmarried/unpartnered female who resides with her own children under 18 years-old.[4] To identify the HH "lead," we select the adult with the highest labor market earnings (with ties broken by higher age, and chosen randomly if tied on age) (Baker et al. 2022; Brady et al. 2017). Appendix II reports similar results with two alternative measures of single motherhood.

Young head includes those in HH's with a lead under 25 years old. *Low education* (using the standardized LIS education variable) is measured as residing in a HH where the lead has less than an upper secondary degree (e.g. a U.S. high school degree). *Jobless* is measured as living in a HH where no members are employed (i.e. non-employment).

[4] This follows other LIS analyses (Brady et al. 2021; Brady and Burroway 2013; Heuveline and Weinshenker 2008; Rainwater and Smeeding 2004; Rothwell and McEwen 2017). Because of constraints in the LIS data and how other countries classify cohabitors, cohabitors are in the reference group. In analyses available upon request, cohabitors are not significantly different (vs. married) for child poverty in the U.S. in 2018.

The penalties are the average marginal effects (AMEs) from logistic regression models predicting child poverty in each of the 30 rich democracies or each wave of U.S data (see Appendix III). The standard errors are adjusted for the clustering of children within HHs. The models also adjust for a standard set of controls commonly included in models of poverty (Baker 2015; Baker et al. 2022; Brady et al 2017; Laird et al. 2018; Zagel et al. 2021): HH *head 25-34 years old* or *over 54* (reference: head 35-53), the *number of children* and *number of adults over 65* in the HH, whether the head had a *tertiary education* (reference: head has secondary education), and whether there are *multiple earners* in the HH. As mentioned above (see fn. 2), we also bound the estimates of the single motherhood penalties while specifying models with other risks and controls omitted.

In the U.S. models, we include additional controls that are not available in all other countries: *single father* HH, and controls for whether the child is *Black*, *Latino*, or *Other* Race (reference: White).[5] Appendix IV shows similar results when adjusting for *immigrant* and *non-citizen heads* on the full sample and Latino subsample (unfortunately, these are not available in every year for the U.S.).

For the U.S. in 2018, descriptive statistics for all HHs, single mother HHs and non-single mother HHs are shown in Appendix III.

Counterfactual Simulations

After estimating penalties and prevalences, we simulate child poverty rates with counterfactual prevalences of single motherhood in the U.S. in 2018.[6] Specifically, the

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[5] Small sample sizes make the coefficients for single father HHs inestimable in some countries, and comparable race/ethnicity data do not exist across countries.
[6] We use the 2018 dataset because the 2019 LIS is the March 2020 CPS-ASEC, collected during the first wave of COVID. Compared to prior years, the 2019 sample is about 15% smaller, had much higher non-response, and was less representative of low-income HHs.

simulations assess how much child poverty would decline with *substantial* reductions in the prevalence of single motherhood by shifting from the actual prevalence (18.94% in 2018) to (i) the cross-national median (14.65%), or (ii) one cross-national standard deviation lower (13.24%). Then, we simulate *dramatic* reductions: (iii) the U.S. in 1970 (10.60%), (iv) one-half the 2018 U.S. (9.47%), or (v) two cross-national standard deviations less (7.54%). Finally, we simulate *eliminating* single motherhood with: (vi) zero prevalence. We conduct the simulations for the entire sample and then by race/ethnicity.

To estimate these simulations, we first predict poverty in the U.S. in 2018 using the logistic regression models (see Appendix III). Second, we estimate predicted probabilities of poverty with counterfactual prevalences of single motherhood. This simulation predicts the mean respondent's probability of poverty based on manipulating the mean respondent's probability of being in a single mother HH (i.e. shifting from the actual probability of single motherhood in 2018 to the counterfactual probabilities). This thought exercise changes the single motherhood status but maintains other predictors at their values. Appendix V reports an alternative counterfactual simulation using random reassignment that yields very similar results.

Obviously, the main estimates of penalties are not causally identified. It is probably unrealistic to reliably identify causal effects of single motherhood or the three other risks with cross-sectional data across 30 rich democracies or 41 years of the U.S. However, we estimate various different models that plausibly bound the estimates of the penalties and simulations. Ultimately, our conclusions remain consistent even if penalties are closer to causally identified and therefore smaller or if penalties are much larger (using plausibly upward biased estimates).

One major reason these estimates of penalties could be biased is because there are stable unobserved differences between children. To get *closer* to causal identification, Appendix VI estimates penalties with four different panel techniques with longitudinal data from the Panel Study of Income Dynamics and Cross-National Equivalent File (PSID-CNEF). These techniques net out stable unobserved differences between children and across time. Appendix VI compares our main single motherhood penalties against these four alternatives. All four produce much smaller penalties. Therefore, these *more* causally identified estimates suggest much smaller single motherhood penalties (Rodriguez Sanchez 2022). In turn, the main estimates are less conservative and give single motherhood a greater chance of playing a substantial role in America's high child poverty.

As previewed above (see fn. 2), we also consider if our estimates of single motherhood penalties are too small. One might argue, contrary to Appendix VI, that the penalty for single motherhood is much more than just the precise causally identified effect. In turn, below we estimate models where single motherhood is the *only* predictor of poverty and the related simulation assumes that *every* characteristic would accordingly change. These are upper bound estimates of the single motherhood penalty (i.e. upwards-biased and inflated), which yield larger reductions in child poverty in our counterfactual simulations. Again, however, we preview that our main conclusions do not change.

RESULTS

We begin by describing how the U.S. compares to other rich democracies and how the U.S. has changed over time in poverty, prevalences and penalties. Doing so clarifies the cross-national and historical variation. Further, these patterns guide our simulations.

Levels and Trends in Child Poverty

For several decades, the U.S. has consistently had one of the highest child poverty rates. Figure 1 shows the U.S. ranks fourth highest among 30 rich democracies with a child poverty rate of 19.8 (horizontal line=U.S.). Recently, Israel, Italy and Spain surpassed the U.S. Still, these four all similarly have very high child poverty. The 95% confidence intervals (CIs) for Italy's and Spain overlap with those for the U.S., and their point estimate are only slightly higher. After the U.S., the fifth highest rate is Greece at 16.5%.[7] The U.S. child poverty rate is almost two standard deviations above the cross-national median of 10.7%.

[FIGURE 1 ABOUT HERE]

This unusually high child poverty rate has been fairly stable over time, as Figure 1 also shows. U.S. Child poverty peaked near 25% 1983-1987. Although the recent cross-national median child poverty rate is 10.7%, the U.S. has always been above 18.5% since 1979. Thus, throughout the past 41 years, the U.S. always had high child poverty. That said, the U.S. has experienced a modest decline in child poverty since 1993.[8]

Cross-National Variation in Prevalences and Penalties

Figures 2 and 3 visualize the prevalences and penalties for the four risks across 30 rich democracies (vertical line=U.S.). Appendix VII provides further detail.

[FIGURE 2 ABOUT HERE]

[7] Appendix XI (Panel A) shows America's high child poverty is principally driven by its lower poverty reduction via taxes and transfers. The U.S. is only 10th highest in market income child poverty, whereas the U.S. is among the lowest in terms of every aspect of poverty reduction. Children in single mother HHs in the U.S. have the 7th highest market income poverty, but the highest post-fisc child poverty.

[8] Appendix XI (Panels B-C) shows the modest decline is principally driven by increasing transfers. Market income child poverty has been fairly stable, while post-fisc child poverty has declined. The rise of transfers and decline in post-fisc child poverty is actually more pronounced among single mother HHs.

[FIGURE 3 ABOUT HERE]

With a prevalence of 18.9%, the U.S. has the twelfth highest prevalence of single motherhood of the 30 rich democracies (Figure 2). Thus, the U.S. is in the middle of the distribution. Also, a fairly high prevalence of single motherhood is typical across rich democracies – the median is 14.7% (see Appendix VII). Further, single motherhood has the least cross-national variation in prevalences among the four risks (cf. CV's in Appendix VII). Thus, most rich democracies have a similar prevalence of single motherhood.

Unlike single motherhood, the U.S. has low prevalences of joblessness and low education (20^{th} and 21^{st} among 30 rich democracies), but the highest prevalence of young headship. Cross-nationally, low education has the highest median prevalence, and young headship has the lowest. That said, the cross-national variation is similar in the prevalences of all three.

Figure 3 shows the U.S. has the highest single motherhood penalty across 30 rich democracies. While single motherhood increases a child's probability of poverty by 9.7 percentage points in the U.S., the cross-national median penalty is only 1.5 percentage points. Thus, the U.S. is *not* distinctive in having the 12^{th} highest prevalence of single motherhood. However, the U.S. *is* distinctive for having the highest penalty for single motherhood.

Indeed, the U.S. has high or moderate penalties for all four risks (for U.S. penalties – with and without U.S. specific controls – see Appendix III). While the U.S. single motherhood penalty is the largest, single motherhood still has the smallest penalty of the four risks in the U.S. and cross-nationally. The largest penalty is for joblessness (5x larger than the single motherhood penalty), followed by low education and young headship.

Single motherhood is also the risk for which the penalty is least commonly significantly positive. Single motherhood is not significantly positive in 24 of 30 countries. Although some non-statistically significant penalties have meaningful positive magnitudes (e.g., Italy), single motherhood is not significantly associated with child poverty in the vast majority of rich democracies. Because a few countries (e.g. the U.S.) severely penalize single mother families, but the single motherhood coefficient is insignificant in most rich democracies, the single motherhood penalty exhibits the most cross-national variation (see Appendix VII). The CV for single motherhood penalties is more than twice as large as the CV in penalties for any other risk. Also, the CV for single motherhood penalties is more than 5x larger than the CV for single motherhood prevalences. Countries differ far more in terms of how much they penalize single mothers than in how many single mothers there are.

Altogether, the cross-national patterns undermine claims that reducing single motherhood would substantially reduce child poverty. The U.S. has only the 12th highest prevalence and a fairly high prevalence is typical. There is far less cross-national variation in the prevalence of single motherhood than in other risks. The U.S. has high penalties for all four risks, but single motherhood actually has the smallest penalty of the four risks. Cross-nationally, single motherhood has the smallest and least reliably significant penalty of the four risks. There is also far more cross-national variation in penalties than prevalences. For single motherhood, the U.S. is unique for having an unusually high penalty not for having a high prevalence.

U.S. Historical Variation in Prevalences and Penalties

In the U.S. 1979-2019, the calculation of prevalences is the same. However, we re-estimate the penalties because the U.S. has data on more variables than the other rich democracies (i.e. single-fatherhood and race/ethnicity). In turn, the penalties are slightly different (see Appendix III).

While U.S. child poverty has been stable at a high level (see Figure 1), Figure 4 shows there have been substantial changes in prevalences. The prevalence of low-educated HHs fell from 27% in 1979 to 10.8% in 2019. The prevalence of young headship also fell from 8.8% to 3.5%. Despite a modest increase up to 1993, the prevalence of joblessness declined from 5.9 to 4.2%. Thus, from 1979 to 2019, the prevalences of three of the four risks substantially declined.

[FIGURE 4 ABOUT HERE]

The prevalence of single motherhood has been fairly stable for several decades, rising only 2.6 percentage points 1979-2019. It rose from 16.3% in 1979 to near 20% 1992-1998 and 2003-2009 and peaked near 21% 2011-2012. But then it declined to 18.9 2018-2019. As a result, the prevalence of single motherhood was lower in 2018-2019 than in 1991. Because the prevalence of the other three risks declined and single motherhood has been stable, single motherhood has been the most common risk in the U.S. since 1991.

Even though both child poverty and the prevalence of single motherhood have been fairly stable since 1979, the two trends did not move together over time. Figure 5 shows both trends indexed so the 1979 values equal 100. While child poverty increased suddenly in the early 1980s, the prevalence of single motherhood rose more slowly. After the 1980s, child poverty mostly declined and stabilized while the prevalence of single motherhood increased and stabilized. Hence, since the 1990s and especially since 2000, child poverty and the prevalence of single motherhood mostly trended in opposing directions.

[FIGURE 5 ABOUT HERE]

Figure 4 also shows the trends in penalties. The penalty for single motherhood peaked in 1986 at 15.2, when it was the third largest. However, the single motherhood penalty has declined since 1986 and been the smallest penalty since 1991. Thus, despite having the largest prevalence, single motherhood has had the smallest penalty for nearly three decades. Like cross-national variation, the historical variation is far greater in penalties than prevalences. In the U.S. 1979-2019, the CV in single motherhood penalties (0.25) is almost four times larger than the CV in prevalences (0.07). Over time, the U.S. has varied far more in how much it penalizes single mothers than in how many single mothers there are.

By contrast, the largest penalty has always been for joblessness, which has modestly increased over time. Hence, even though joblessness has the second lowest prevalence of the four risks, its penalty is about 5.6 times larger than the penalty for single motherhood. That said, the historical variation in single motherhood penalties is much larger (i.e. 1.7-3.1x) than the historical variation in penalties for the three other risks.

Altogether, trends in the U.S. 1979-2019 also undermine claims that reducing single motherhood would substantially reduce child poverty. While single motherhood became the most common of the four major risks, this is because the other risks declined while the prevalence of single motherhood has been stable. The trends in child poverty and the prevalence of single motherhood have moved in opposing directions in recent decades. Single motherhood has also had the smallest penalty of the four risks since 1991.

Simulations of 2018 U.S. Child Poverty

Before the simulations, it is valuable to describe how children in single mother and couple HHs differ (Appendix III). In 2018, children in single mother families have a much higher poverty rate of 43.7% while child poverty rate in couple HHs is 13.1%. On the surface, this suggests that if children in single mother HHs shifted to couple HHs, the child poverty rate would decline substantially. However, this raw unconditional difference overstates the impact of single motherhood because single motherhood is confounded with other risks. Children in single mother HHs are also more likely to be in low-educated HHs (15.2% vs. 10.2% in couple HHs), jobless HHs (12.8% vs. 2.4%) and young-headed HHs (8.3% vs. 2.3%). Children in single mother HHs are also less likely to be in multiple earner and high-educated HHs, have slightly fewer children, and are more likely to be Black and less likely to be Latino. Moreover, even with the poverty rate of coupled HH's, that "floor" of 13.1% would still be above the cross-national median of 10.7%. Hence, U.S. has high child poverty even in coupled HHs.

Using the logistic regression model for the U.S. in 2018 (Appendix III), Figure 6 displays the simulated probability of child poverty with counterfactual prevalences. For comparison, Figure 6 also includes the countries with the three highest, the fifth highest, the median, and the lowest child poverty countries. The actual and predicted values show the U.S. has the fourth highest child poverty rate. To assess how much the simulations would reduce America's high child poverty, we emphasize how the U.S. would rank among the 30 rich democracies and compare to the median child poverty rate.

[FIGURE 5 ABOUT HERE]

With all six counterfactual prevalences of single motherhood, the child poverty rate would only decline modestly. This is the case regardless of whether the prevalence of single motherhood is reduced substantially or dramatically, or even if single motherhood is eliminated. If the U.S. substantially reduced the single motherhood prevalence to the cross-national median (14.7%) or one cross-national standard deviation less (13.2%), child poverty would only decline to 18.6-18.7%. If the U.S. dramatically reduced the prevalence of single motherhood to the prevalence in 1970 (10.6%), one-half of the 2018 prevalence (9.5%) or two cross-national standard deviation less (7.5%), the child poverty rate would still be 18.1-18.4%. Even if single motherhood was eliminated (i.e. a prevalence of zero), child poverty would only decline about

2.3 percentage points from 19.8% to 17.6%.

Thus, every counterfactual simulation shows that reducing the prevalence of single motherhood would not substantially reduce child poverty in the U.S. Regardless of the simulation, the U.S. would not change from having the 4th highest child poverty. As noted above, the CI's for Italy and Spain's child poverty rates (i.e. 2nd and 3rd highest) overlap with the CIs for the U.S. child poverty rate. In all simulations, the CIs for the U.S. would continue to overlap with Italy's CIs. Spain and the U.S.'s CIs would overlap in all simulations except with zero prevalence. Across simulations, the U.S. would always have a child poverty rate more than 1.4 standard deviations above the cross-national median. Thus, regardless of how much the prevalence of single motherhood is reduced, the U.S. would continue to have high poverty compared to other rich democracies.

Figure 7 simulates the trends in child poverty in the U.S. 1979-2019. Here we focus on one dramatic reduction to the 1970 prevalence and the elimination of single motherhood (i.e. prevalence of zero). Even if the prevalence of single motherhood was reduced dramatically or eliminated, the U.S. would never have had significantly lower child poverty over the past four decades. The only year that could have placed the U.S. below Greece's recent child poverty rate (i.e. 5th highest) would be if there was zero prevalence of single motherhood in 2013. In that simulation, the 16.3% child poverty rate would still have been 1.15 standard deviations higher than the cross-national median. In short, the U.S. child poverty rate 1979-2019 would have been very similar with dramatically lower or zero prevalence of single motherhood.

[FIGURE 6 ABOUT HERE]

Simulations by Race/Ethnicity

Table 1 displays simulations of counterfactual prevalences of single motherhood for White, Black, and Latino children in the U.S.[9] The prevalences of single motherhood are much higher among Black (42.4%) and Latino (21.5%) than White children (12.7%). The prevalence of single motherhood among White children is actually below the cross-national median (i.e. 14.7%, Appendix VII). The single motherhood penalty is slightly higher among Latino children (9.2%). Consistent with other research (Baker 2022; Brand et al. 2019; Cross 2019), the single motherhood penalty is lower among Black than White children (6.6% vs. 8.9%).

[TABLE 2 ABOUT HERE]

The next rows show the actual and predicted child poverty rates. At 11.4%, White children in the U.S. have child poverty rates closer to the cross-national median. However, Black (34.9%) and Latino (31.0%) children have extremely high child poverty rates – far higher than any rich democracy has had in almost five decades of LIS data.[10] Indeed, Black children have a poverty rate 12.3 percentage points and 2.4 standard deviations higher than Israel. Because White children have child poverty rates near the cross-national median, most of America's high child poverty is attributable to extremely high Black and Latino child poverty.

The remaining rows display child poverty rates by race/ethnicity with three counterfactual prevalences of single motherhood: the substantially lower cross-national median, the dramatically lower U.S. in 1970, and zero. Reducing prevalences to the cross-national

[9] Appendix VIII replicates this for Native American and Asian children. The sample sizes are small, but reductions in single motherhood would not reduce Native-White or Asian-White racial inequalities either.

[10] Appendix XI (Panel E) shows Black and Latino children are disadvantaged compared to white children in nearly every component (i.e. market income and almost all transfer categories). This is the case for all children and children in single mother HHs.

median yields only slightly lower child poverty rates. With 1970 U.S. prevalence, the poverty rate would also decline only modestly across all racial/ethnic groups. With both cross-national median and 1970 prevalences, Black and Latino child poverty rates would still be nearly three times higher than the cross-national median. Even with zero single motherhood, the declines in child poverty would be modest. If there was zero single motherhood, the poverty rate among Black (31.4%) and Latino children (28.9%) would still be extremely high.

Lower prevalences of single motherhood would also not reduce racial inequalities in child poverty. Recall, White children already have child poverty rates close to the cross-national median. Reducing the prevalence for single motherhood among White children would push their poverty rates below the cross-national median. However, with zero single motherhood, the relative ratio between Black and White child poverty would modestly increase from its actual 3.1 to 3.2. If there was zero prevalence of single motherhood, the Latino-White relative ratio in child poverty rates would increase from 2.7 to 3.0. On balance, the absolute differences in poverty rates would be modestly smaller if there was zero prevalence of single motherhood.

This lack of decline in racial inequalities partly results from the smaller single motherhood penalty for Black children. However, the lack of decline in racial inequalities is also because Black and Latino children have high poverty even in coupled HHs. Black and Latino children in coupled HHs still have high poverty rates of 15.3% and 24.8%, while White children in coupled HHs have a poverty rate of only 6.9%. Therefore, shifting children from single mother to coupled HHs would not reduce racial inequalities in child poverty.

Simulations with Alternative Estimates of Single Motherhood Penalties

On the one hand, recall Appendix VII shows that plausibly more causally identified penalties would be much smaller, which would mean much smaller simulated reductions in child poverty. On the other hand (see fn. 2), if other independent variables mediate the effect of single motherhood on child poverty, this could conceal some of the single motherhood penalty. Perhaps single motherhood significantly reduces employment. If so, including joblessness and multiple earners in the model could block the causal pathway between single motherhood and child poverty (Elwert and Winship 2014), and attenuate the single motherhood penalty. If the single motherhood penalty is truly much larger than our estimates, lower prevalences of single motherhood could substantially reduce child poverty.

Before proceeding, it is important to temper this concern. Brady and colleagues (2021) explain that defining single motherhood penalties as the direct effect on poverty net of other risks and controls suffers less bias. First, the effect of single motherhood on employment is probably not very large. This is because employment is overwhelmingly the norm among single mother HHs in the U.S. (Biegert et al. 2022). Among children in single mother HHs, 87.2% have at least one earner. Second, single motherhood likely mediates the effects of other risks as much as other risks mediate single motherhood. For instance, considerable evidence shows low education contributes to single motherhood (Boertien and Bernardi 2022; Cross 2019; Ellwood and Jencks 2004; Harkonen 2018; Hogendoorn et al. 2020; McLanahan 2004). Moreover, joblessness and single motherhood likely reciprocally cause each other. If so, the correct specification is to include both variables in the model (Elwert and Winship 2014). Third, models of the relationship between single motherhood, employment, and poverty trigger a tradeoff between posttreatment control versus omitted variable bias and unobserved confounding (Brady et al. 2021). Even if joblessness blocks some of the causal pathway between single motherhood and poverty, joblessness is by far the dominant risk of poverty. Therefore, even if omitting joblessness reduces posttreatment bias, omitting joblessness would trigger unobserved confounding and upwardly bias the single motherhood penalty.

Given this tradeoff, we re-estimate the simulations with estimates of the single motherhood penalty using alternative specifications and an alternative measure of employment. We underline that the single motherhood penalty should increase because of omitted variable bias regardless of reducing posttreatment control. Therefore, these alternative single motherhood penalties are probably inflated. The critical question is what happens to the simulations when we combine these inflated penalties with lower prevalences of single motherhood.

Appendix IX's first column displays the main results (cf. Appendix III and Figure 6). The second column omits every other independent variable, presuming single motherhood is the *only* cause of child poverty. The third omits the employment, education and age of head variables but retains other controls. This removes variables that most could be endogenous to single motherhood. The fourth measures employment intensity as the number of full-time employees (FTE, i.e. 40 hours × 52 weeks) per working-age adult (Baker et al. 2022).[11]

Unsurprisingly, the penalty for single motherhood is higher in models 2-4 (i.e. 10.1-29.4 vs. 8.8). Again, we conjecture these alternative penalties are inflated by omitted variable bias. Indeed, *any* other specification with more controls reduces the single motherhood penalty.

However, even with these inflated penalties, reducing the prevalence of single motherhood still results in the U.S. maintaining high child poverty. With these inflated penalties,

[11] While the main results hold constant other characteristics, the first alternative unrealistically assumes *every* characteristic would change from the mean of single mother HHs to the mean of coupled HHs (e.g. from 13% jobless to 2%, 15% low-educated to 10%, 8% young headship to 2%, and from 15% Black to 9% Black, etc.). The second assumes the mean employment, education, and age of single mother HHs would change to the means of coupled HHs while other controls would remain unchanged. The third assumes the characteristics of single mother HHs would remain unchanged, including the employment intensity.

the counterfactual simulations reveal only slightly lower poverty than Figure 6. With the cross-national median prevalence, the U.S. would still have the 4th highest child poverty rate. With a prevalence of zero, and using these inflated estimates of the penalty, the U.S. would still have a child poverty rate of 14.3-17.1%. The U.S. would still be 4th to 7th highest and 0.73 standard deviations above the cross-national median. Thus, even with these inflated single motherhood penalties and zero single motherhood, the U.S. would still have high child poverty.

CONCLUSION

Many have long argued single motherhood is a central cause of child poverty and that reducing single motherhood would substantially reduce America's high child poverty. Applying the PP framework, we analyze recent LIS data for 30 rich democracies and for the U.S. 1979–2019. We then simulate how much U.S. child poverty could be reduced with counterfactual prevalences of single motherhood. We also examine results by race/ethnicity.

U.S. child poverty has been stable and high for decades and is fourth highest across 30 rich democracies (Brady 2023). However, several descriptive patterns contradict the importance of single motherhood. At 12th highest of 30 rich democracies, the U.S. has a fairly typical prevalence of single motherhood. Indeed, most rich democracies have a similar prevalence and there is less cross-national variation in the prevalence of single motherhood than in the prevalences of the other major risks. There is also far more variation in single motherhood penalties than prevalences. Single motherhood is the most common risk of the four major risks in the U.S., but this is because the other major risks declined while the prevalence of single motherhood has been stable. In addition, child poverty and the prevalence of single motherhood have moved in opposite directions in recent decades.

The U.S. has the highest penalty for single motherhood across rich democracies, and penalties vary far more than prevalences across countries and over time within the U.S. The penalty for single motherhood has been the smallest of the four risks cross-nationally and in the U.S. since 1991. Nevertheless, our study confirms the distinctively high penalty for single motherhood in the U.S. (Brady and Burroway 2012; Maldonado and Nieuwenhuis 2015; Misra et al. 2012). The unusually high penalty for single motherhood plays a larger role than the prevalence of single motherhood for America's high child poverty.

The counterfactual simulations assess the potential impact of a lower prevalence of single motherhood. All simulations reveal that reducing single motherhood would not substantially reduce child poverty. Child poverty would only decline modestly if the U.S. substantially or dramatically reduced the prevalence of single motherhood. Even if there was zero single motherhood in the U.S., the U.S. would not change from having the fourth highest child poverty rate among 30 rich democracies. If the U.S. dramatically reduced or eliminated single motherhood, the 41-year trend 1979-2019 in child poverty would be very similar.

Lower prevalences of single motherhood would not reduce racial inequalities in child poverty. While Black and Latino children have a higher prevalence of single motherhood and high child poverty, lower prevalences would only modestly reduce Black and Latino child poverty. Even at zero prevalence of single motherhood, Black and Latino child poverty rates would remain extremely high. Moreover, we highlight the high rates of child poverty even among Black and Latino *married/coupled* HHs. Rather than focusing on single motherhood, we emphasize the systemic racial inequality in child poverty that exists regardless of single motherhood (Baker 2022; Baker et al. 2022; Baker and O'Connell 2022; Williams 2019; Williams and Baker 2021).

There are a few plausible reasons why our findings contrast with prior simulations. First, we eschew the flawed OPM often used in prior studies (see Appendix I). Second, prior studies examined an arguably atypical and unrepresentative moment in recent U.S. history. The 1980s featured an unusual combination when child poverty rates and the single motherhood penalty were *peaking* and the prevalence of single motherhood had risen. Our longer term perspective reveals that child poverty and the single motherhood penalty declined from that peak. Moreover, both the prevalence of single motherhood and high child poverty were fairly stable over time but trended in opposing directions. Since the 1980s, the U.S. prevalence became increasingly typical compared to other rich democracies. Third, prior studies often estimated penalties as raw unconditional differences in the poverty of single mother versus coupled HHs. Because single motherhood is confounded with other risks, we advocate for estimating penalties conditional on other risks and predictors. Fourth, our replication code enables other researchers to precisely identify any other differences.

While our results suggest single motherhood does not play a large role in America's high child poverty, it is important to acknowledge that single motherhood still could play a role in rising economic inequalities and other adverse child well-being consequences. Especially less educated single mothers are falling behind dual-income, high-educated, married couples, and this has implications for the resources for and investments in their children. As well, of course, our study does not mean there are no adverse consequences for child health, development and well-being. We point out that reducing the poverty of children in single mother households could potentially reduce these other adverse consequences as well. However, this study does not rule out direct effects of single motherhood on such consequences. Of course, there are also many reasons to make birth control more accessible to prevent especially young single motherhood.

Finally, this study informs social policy debates. First, policymakers often intervene to discourage divorce and non-marital births and to encourage marriage. Because lower prevalences can play only a modest role, our study suggests this can have only limited impact on child poverty. Second, because the U.S. has the highest single motherhood penalty, more generous social policies could feasibly reduce this penalty (Brady 2023). Countries reduce child poverty with a variety of transfers (see Appendix XI). Because the U.S. reduces child poverty comparatively little in all kinds of transfers, there are many specific social policies that could make a difference. For instance, the Biden administration's expanded child tax credit reduced child poverty more than any reduction in the prevalence of single motherhood could accomplish (Parolin et al. 2022). Indeed, Appendix XI (Panel F) shows the penalty for single motherhood was less than half as large in 2021 during the expanded CTC as in 2018.[12] In addition to publicly financed transfers, child poverty could be reduced by greater alimony and child support payments, which have been flat while transfers have expanded in recent decades (see Appendix XI, Panels C-D). Ultimately, rather than asking why single mother HHs are formed or intervening to discourage single motherhood, it would be more productive to address the extreme racial inequality in child poverty and reduce the high penalty the U.S. distinctively attaches to single mother HHs.

[12] In 2021, the penalty for low education and the coefficients for the number of children, single father HH, and being Black or Latino were considerably smaller as well.

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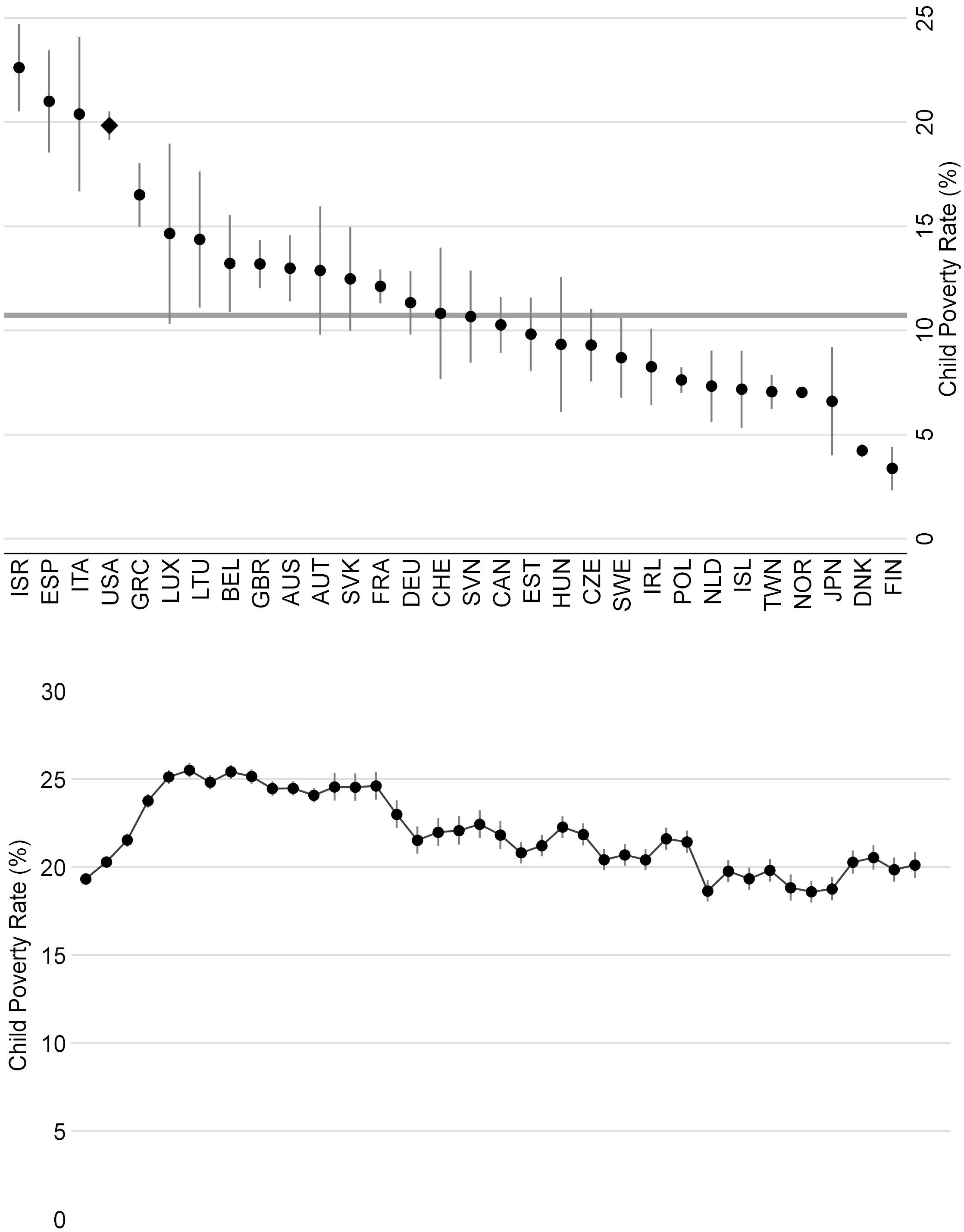


Figure 1. Child Poverty Rates Across 30 Rich Democracies (upper panel) and Within U.S. 1979-2019 (lower panel).

Note: In upper panel, horizontal line=median child poverty rate and vertical lines=95% confidence intervals.

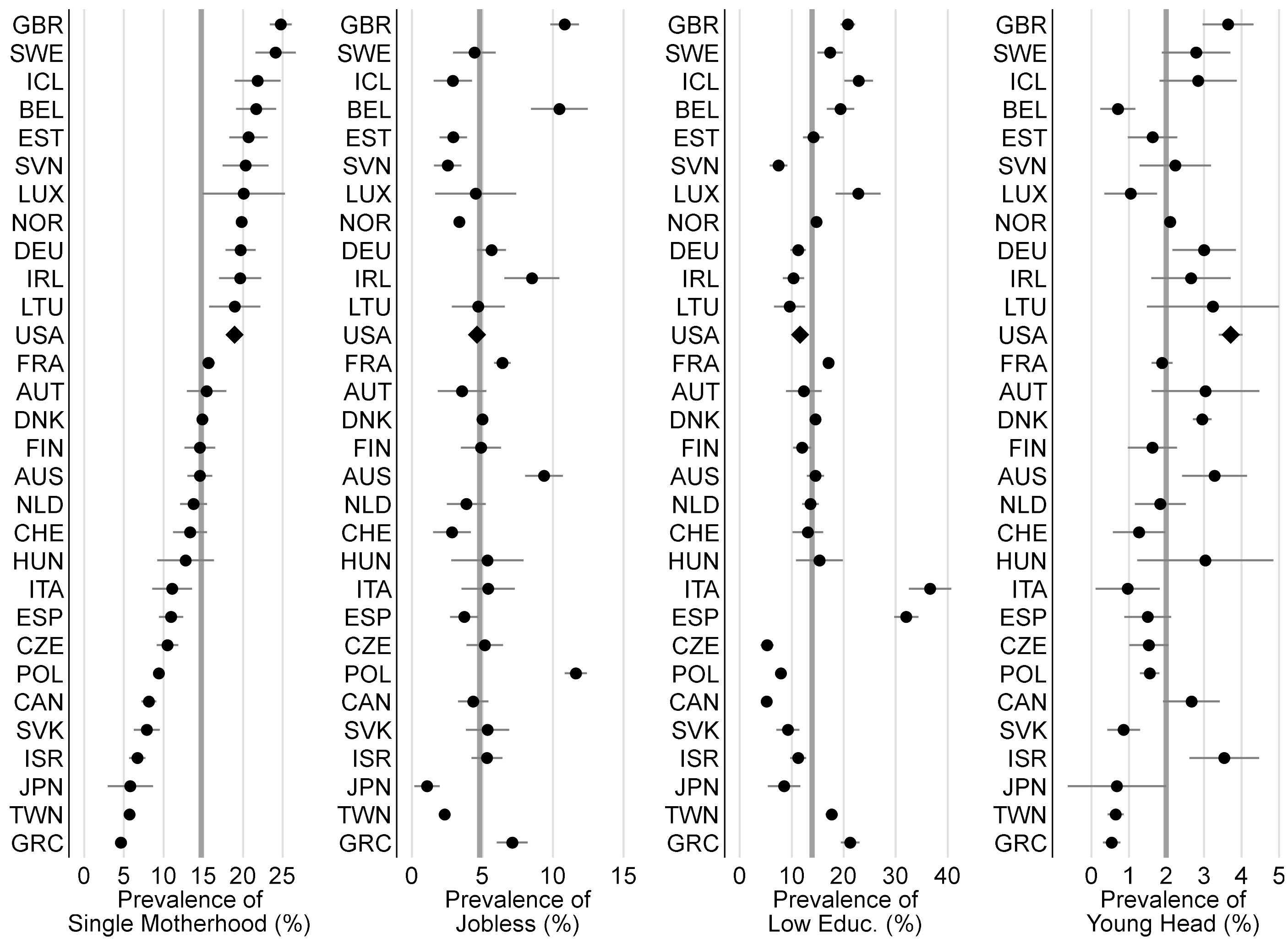


Figure 2. Distribution of Prevalences Across 30 Rich Democracies in Recent LIS Data.

Notes: Vertical lines represent median prevalences. Horizontal lines represent 95% confidence intervals.

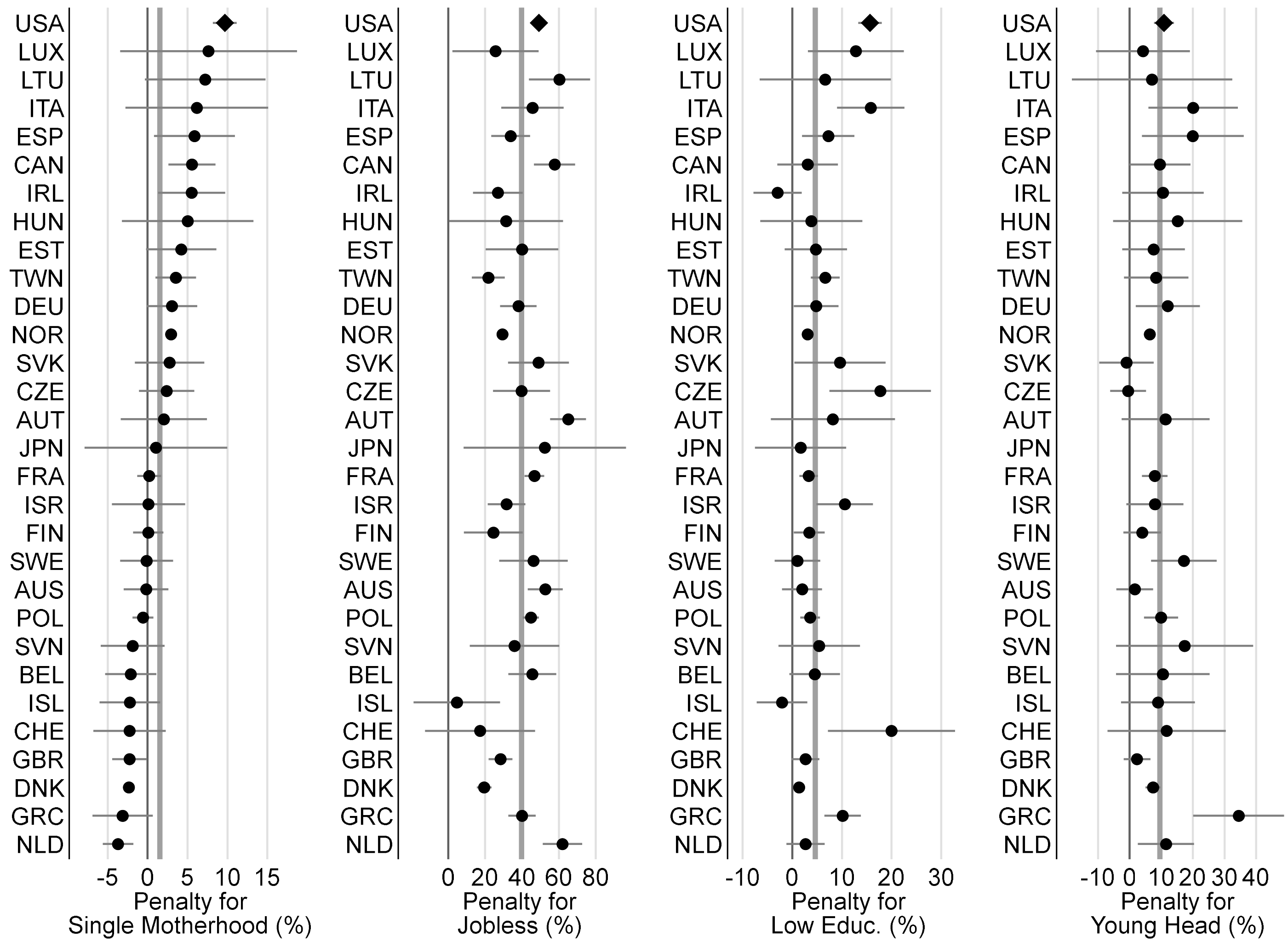
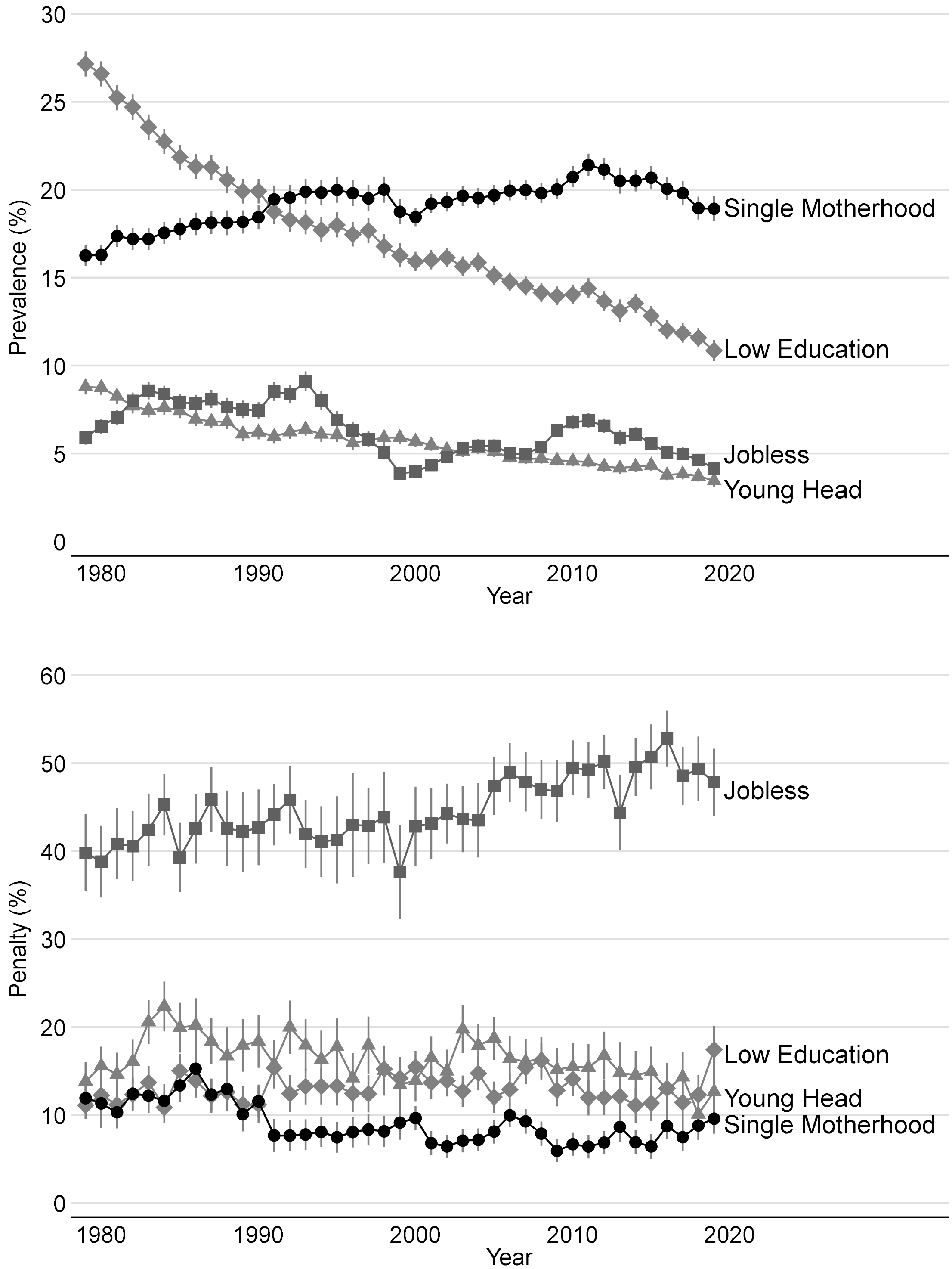


Figure 3. Distribution of Penalties Across 30 Rich Democracies in Recent LIS Data.
Notes: Vertical lines represent median penalties. Horizontal lines represent 95% confidence intervals.



<u>Figure 4.</u> Trends in the Prevalences (upper panel) and Penalties (lower panel) of the Four Risks Child Poverty in the U.S. 1979–2019 in Recent LIS Data.
Note: Vertical lines represent 95% confidence intervals.

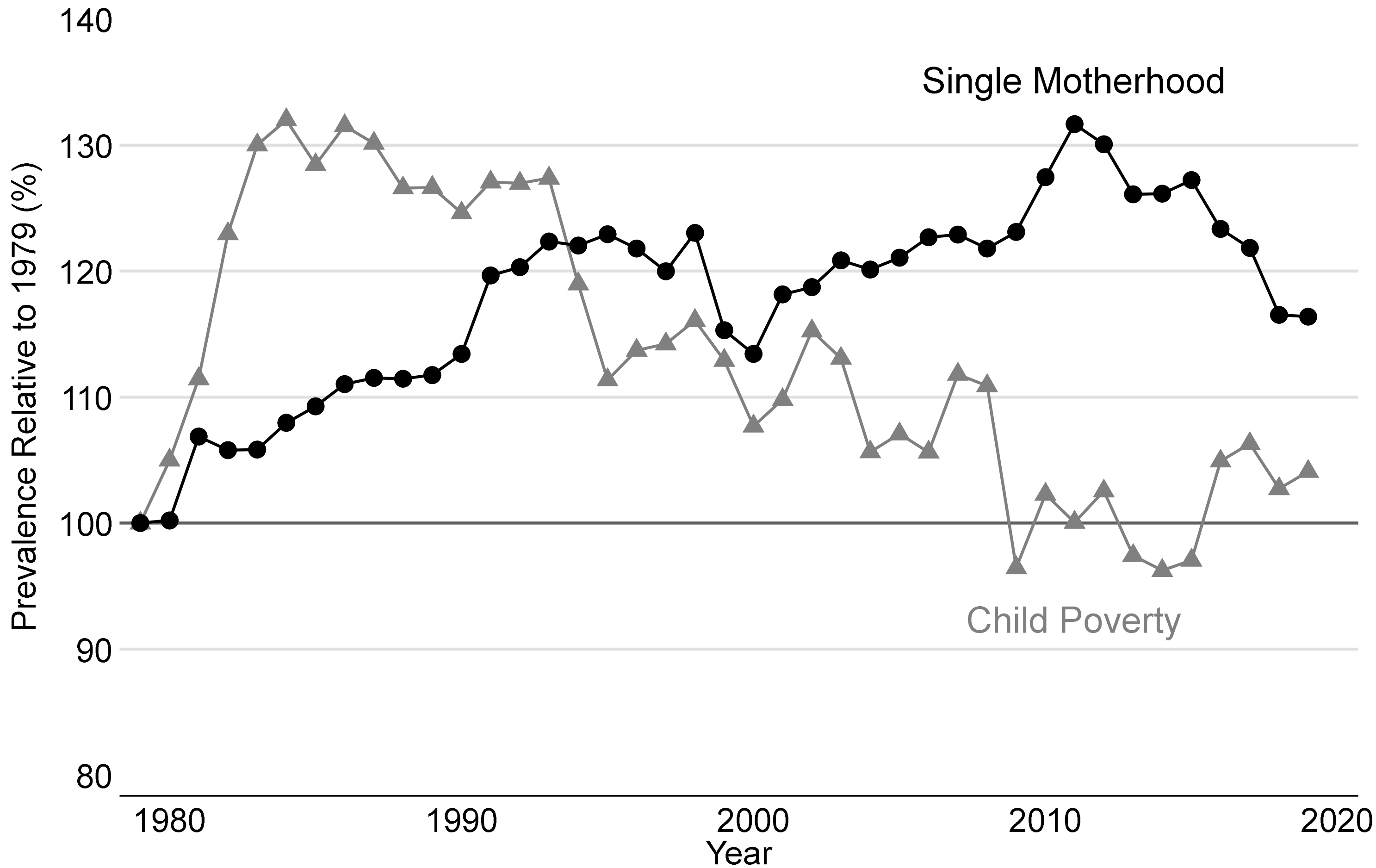


Figure 5. Trends in Child Poverty and the Prevalence of Single Motherhood in the U.S. 1979–2019, Indexed to 1979=100.

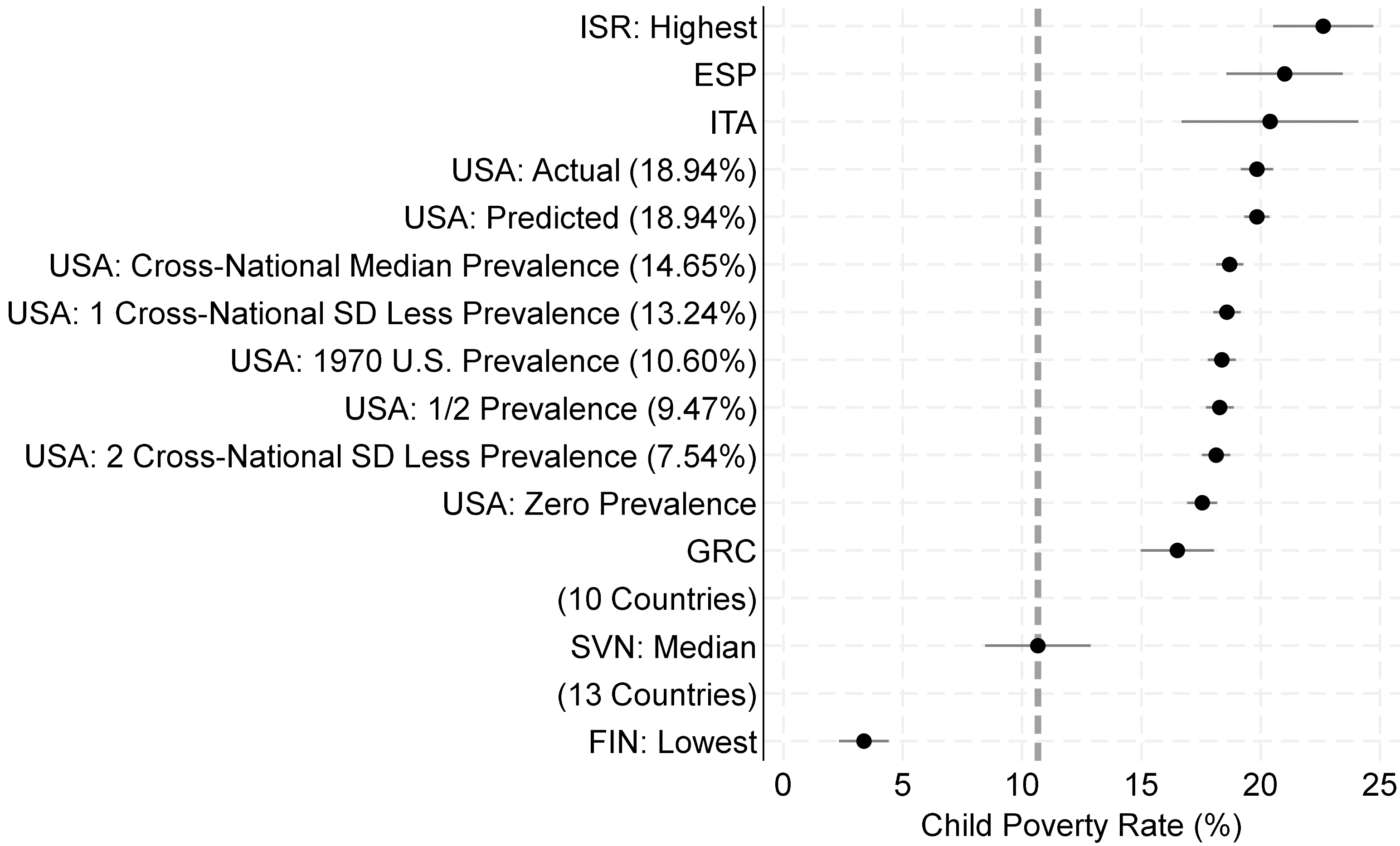


Figure 6. Child Poverty in the U.S. (2018) with Actual, Predicted, and Simulations Based on Counterfactuals Prevalence of Single Motherhood (in Parentheses).

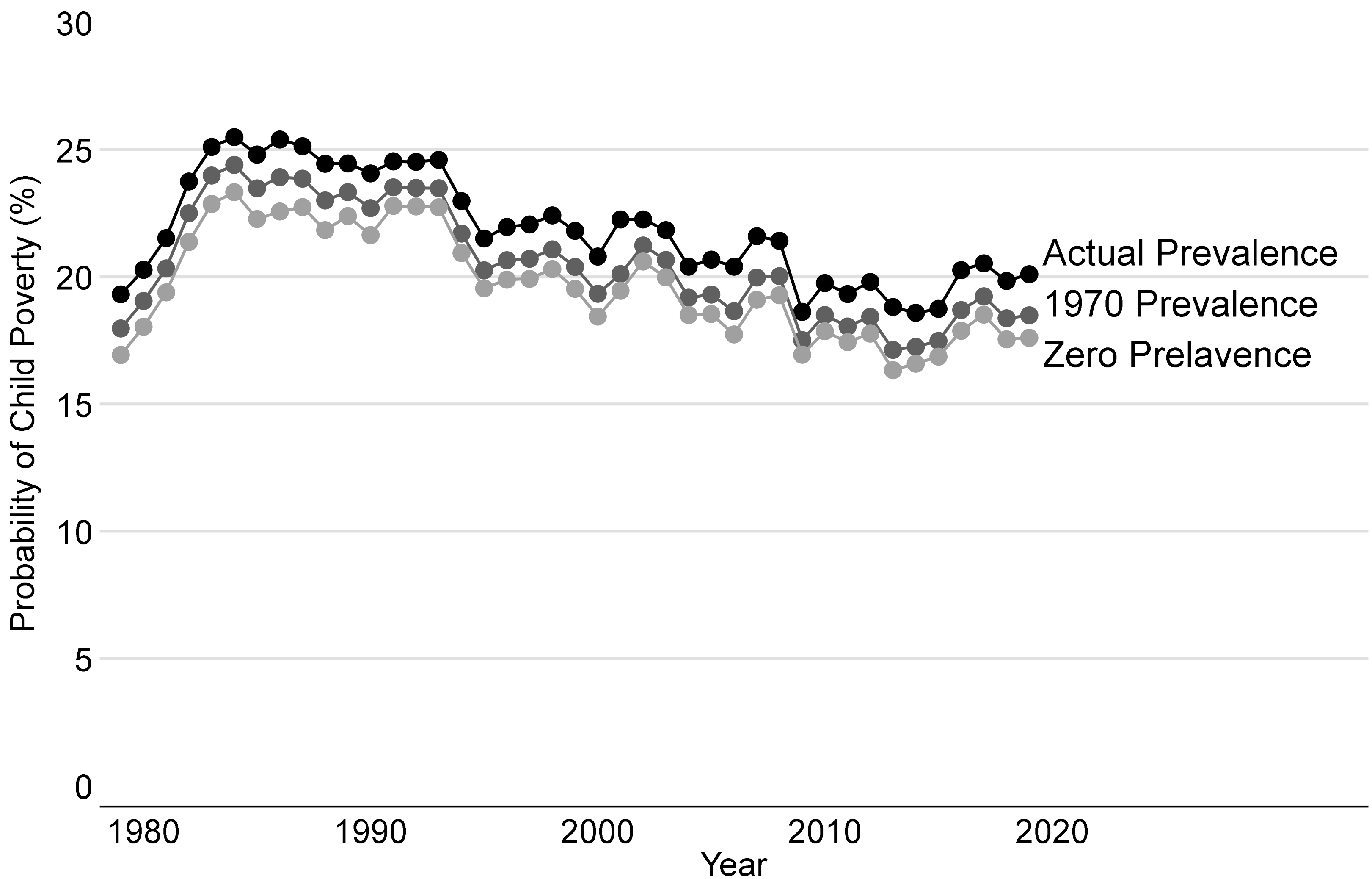


Figure 7. Trends in Actual Child Poverty and Simulated Child Poverty Based on Counterfactuals Prevalence of Single Motherhood in the U.S. 1979–2019.

Table 1. Racial Decomposition of Prevalences and Penalties of Single Motherhood, and Predicted Child Poverty with Simulations Based on Counterfactual Prevalences of Single Motherhood in the U.S. 2018.

	White Children (N=26,234)	***Black Children (N=4,741)***	***Latino Children (N=11,199)***
Prevalence of Single Motherhood (%)	12.72	42.43	21.51
Penalties for Single Motherhood (%)	8.93 (6.89-10.97)	6.57 (1.94-11.28)	9.20 (5.86-12.54)

	White Child Poverty (%)	***Black Child Poverty (%)***	***Black-White Ratio***	***Latino Child Poverty (%)***	***Latino-White Ratio***
Actual	11.42	34.85	3.05	31.04	2.72
Model Predicted	11.42	34.85	3.05	31.04	2.72
Cross-National Median Single Motherhood Prevalence	10.75	32.37	3.01	30.17	2.81
1970 U.S. Single Motherhood Prevalence	10.46	32.11	3.07	29.81	2.85
Zero Single Motherhood	9.71	31.44	3.24	28.89	2.98

Notes: Penalties for all three groups are statistically significant at .001 level.

<u>Appendix I.</u> Justification for Relative Poverty Measurement and Alternative Poverty Measures *(the second and third paragraphs in this Appendix include some material that has been published in Brady [2023]. We repeat and reiterate some of those arguments here solely to provide a summary of the case against the OPM)*.

As explained in the text, we define poverty as relative to the prevailing standards of living and consumption within each country-year (Fremstad 2020; Gornick and Jäntti 2012; Rainwater and Smeeding 2004; Smeeding 2016). Poverty is a shortage of resources compared to needs (Smeeding 2016), and both resources and needs are defined in the context of a time and place. Especially the international poverty and poverty measurement literatures have justified relative poverty measures for at least four decades (see Baker et al. 2022; Brady and Burroway 2012; Brady et al. 2017; Fremstad 2020; Gornick and Jäntti 2012; Heuveline and Weinshenker 2008; Rainwater and Smeeding 2004; Smeeding 2016; Zagel et al. 2021). Therefore, we only briefly mention that the literature offers at least four reasons that relative poverty measures are preferred over alternatives. First, relative measures demonstrate better predictive validity in well-being, health and life chances. Second, relative measures are more reliable across countries and over time. Third, relative measures are more consistent with leading conceptualizations of poverty like capability deprivation and resources versus needs. Last, but not least, absolute measures with fewer or less salient problems have not been developed.

As explained in the text, we eschew the deeply flawed OPM. Reiterating Brady (2023), the OPM thresholds are widely understood to be far too low and the family size adjustments are incoherent (Baker et al. 2022; Fremstad 2020; O'Connor 2001; Rainwater and Smeeding 2004; Smeeding 2016). In addition, the OPM's definition of income ignores taxes and tax credits, and inconsistently includes some transfers but omits others (National Academies of Sciences, Engineering, and Medicine 2019). For example, Temporary Assistance for Needy Families (TANF) counts as income, but the Supplemental Nutritional Assistance Program (SNAP), housing subsidies, childcare vouchers, and tax credits like the Earned Income Tax Credit (EITC) and Child Tax Credit (CTC) do not. Since the 1990s, the EITC grew into the largest assistance program for families with children. Government spending on each of SNAP, the EITC and the CTC is now dramatically larger than on TANF. Moreover, single mother families disproportionately receive SNAP and the EITC (Laird et al. 2018). Therefore, over-time comparisons based on the OPM, especially for child poverty, are particularly unreliable. Because the LIS income measure comprehensively includes all income sources, transfers, and taxes, it is also impossible to exactly apply the OPM threshold to this income measure.

Reiterating Brady (2023), we note that despite some popular impressions, the OPM was problematic from the beginning. The OPM is often attributed to Orshansky. However, O'Connor (2001: 184) explains, "No one was more surprised, though, than Orshansky herself, who had never meant her measures as official government standards. Concerned primarily with suggesting a way to vary the measure for family size, Orshansky took pains to recognize that her work was at best an 'interim standard,' 'arbitrary, but not unreasonable,' and minimalistic at best." In *The Undeserving Poor*, Katz (1989: 116) quotes Orshansky as writing, "'The best that can be said of the measure,' she wrote, 'is that at a time when seemed useful, it was there.'" The standard of needs underlying the OPM never had a clear scientific basis (Fremstad 2020; Katz 1989; O'Connor 2001). Using data from the mid-1950s, Orshansky developed a rule of thumb that food amounted to roughly one-third of expenses for typical HHs on average. The evidence was never clear that this applied to low-income HHs, however. Further, the Johnson administration ended up using the "economy food plan", which was about 25% below the "low-cost food budget" used by Orshansky (Katz 1989). The economy food plan was meant for emergencies and on a temporary basis. Also, the food budgets were not subsequently revised. In the late 1960s, the government began updating the OPM thresholds using the consumer price index rather than calibrating the thresholds according to changing food budgets. This had the consequence of severing any tie to the food budget as a standard of needs. Indeed, Katz (1989: 116) quotes Orshansky as writing: “This meant, of course, that the food-income relationship which was the basis for the original poverty measure no longer was the current rationale.” Moreover, and as is well known, food is certainly much less than 1/3rd of HH expenses today. As a result, the OPM effectively ignores the increased costs of important household needs like childcare and healthcare, which were less essential or much cheaper when the OPM was created.

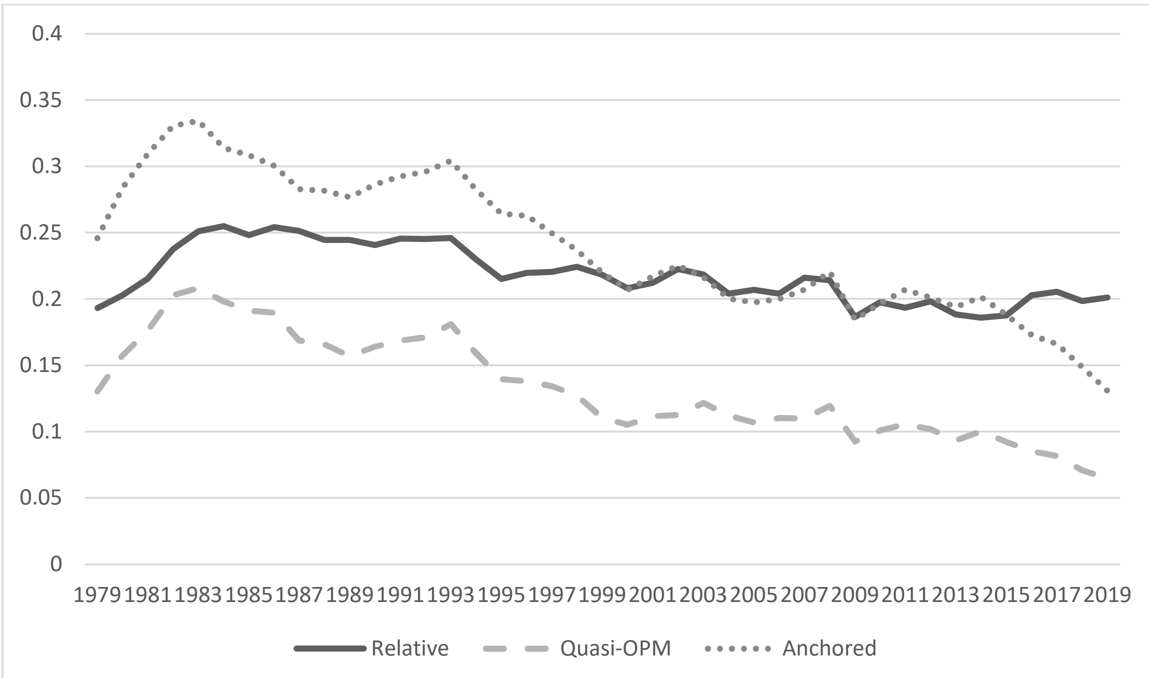
Unfortunately, prior relevant U.S.-specific studies cited in the text mainly use the OPM (e.g. Ananat and Michaels 2008; Cancian and Reed 2009; Iceland 2019; Lerman 1996; Lichter et al. 2003; Lichter et al. 2005; Musick and Mare 2004; Sigle-Rushton and McLanahan 2002). For instance, Eggebeen and Lichter (1991) use an inflation-adjusted 1987 OPM threshold and a relative measure. However, even their relative measure is based on the OPM’s family size adjustments and income definition. Because they use the OPM’s income definition, they omit taxes, tax credits like the EITC and CTC, and near-cash transfers like SNAP. Similarly, Thomas and Sawhill (2002) expand the income definition by adjusting for federal taxes, work-related childcare expenses, SNAP and the EITC. However, they appear to use the flawed OPM thresholds with this income definition.

Despite the OPM’s problems and the arguments for a relative measure, we tested two alternative poverty measures on the U.S. data. The first we call a “quasi-OPM” measure. As best we can tell, this appears to be similar to Thomas and Sawhill’s (2002) measure. Unfortunately, it is not possible to apply the OPM exactly in the LIS. The LIS “lissifies” the CPS-ASEC and aggregates several welfare benefits into categories. For example, the LIS combines TANF, WIC, EITC and CTC into one variable “family benefits” (HI41). As well, we would have to remove SNAP (which is a different LIS variable) from the broader income variable (DHI) used to construct poverty. So, ultimately, the LIS does not compile the income variables such that one can recreate the OPM income definition. For these reasons, to the best of our knowledge, we are not aware of any LIS working paper using the OPM with LIS data. While one could analyze the OPM with the CPS, this would force us to abandon the higher quality income data in the LIS.

Because we cannot recreate the OPM income definition within the LIS, we use the LIS income definition with a threshold very close to the OPM thresholds. This means we use the household rather than the “family” like the OPM, which is justified given every scholar we ae aware of critiques the family unit in the OPM (see e.g. the two NAS reports). The OPM has dozens of different thresholds for different family sizes and compositions each year (see mention of the incoherence of family size adjustments above). To standardize the OPM threshold per individual, we take the OPM thresholds for a family of four in 2019 and equivalize that threshold by the square root of household members. We then convert that threshold to current dollars in each year 1979-2019. Then, poverty equals having less equivalized post-fisc income than this quasi-OPM threshold.

Second, we construct an anchored measure (see e.g. Chen and Corak 2008; Smeeding 2016). We choose the midpoint year of 2000. Using the relative poverty threshold for 2000, we then convert that dollar amount to constant 2019$. This “anchors” the threshold of needs and/or consumption standards according to what they were in 2000 and applies that same threshold for all years regardless of how needs and/or consumption standards changed 1979-2019. Then, poverty equals having less equivalized post-fisc income than this anchored threshold.

Panel A shows the trends in relative, quasi-OPM and anchored poverty in the U.S. 1979-2019. As expected, the two more "absolute" poverty measures show marked declines over time – contrary to the more stable relative measure. Similarly, the more anchored measure naturally report much higher poverty rates early versus later in the period.



Panel A. Trends in Poverty with Relative, Quasi-OPM and Anchored Measures in the U.S. 1979-2019.

Compared to the relative measure, these more "absolute" measures show much lower poverty in recent years. For instance, in 2018, 19.84% of children are relatively poor. By contrast, only 6.5% of children are poor with the quasi-OPM measure and 13.1% are poor with the anchored measure. Please recall the quasi-OPM is much lower than the OPM because this income definition includes tax credits and transfers ignored by the OPM.

Panel B replicates three simulations from Table 1 with the alternative poverty measures. These results as substantively consistent with Table 1. To make these analyses comparable, one has to compare the single motherhood penalty and simulated poverty rates to the actual for each measure (i.e. the % of actual in parentheses). The counterfactual simulations with quasi-OPM and anchored poverty are very slightly larger (relative to the base actual child poverty rate) than those with the relative measure. Yet, across all three, the simulation with zero single motherhood would only reduce child poverty to 89.5-92.6% of the actual level. Indeed, we emphasize that the confidence intervals for the predicted values would show percentages of the actual child poverty rate that overlapped across the three measures.

Panel B. Simulations of Alternative Measures of Child Poverty Rates with Counterfactual Prevalences of Single Motherhood in the U.S. 2018.

	Relative Child Poverty Rate (% of Actual)	***Quasi-OPM Child Poverty Rate (% of Actual)***	***Anchored Child Poverty Rate (% of Actual)***
Actual	19.84	7.07	14.86
Cross-National Median Single Motherhood Prevalence (14.65%)	18.70 (94.25%)	6.45 (91.23%)	13.82 (93.00%)
1970 U.S. Single Motherhood Prevalence (10.60%)	18.37 (92.59%)	6.33 (89.53%)	13.58 (91.39%)
Zero Single Motherhood	17.55 (88.46%)	6.05 (85.57%)	12.96 (87.21%)
Penalties (*100)	8.8 (44.35%)	2.9 (41.02%)	6.2 (41.72%)

Notes: All models are otherwise identical to Table 1. The penalties are all statistically significant (p<.001).

Moreover, the single motherhood penalty is actually *largest* for the relative poverty measure (44.4% vs. 41-41.7% compared to the base actual poverty rates). That is, the relative poverty measure shows the largest coefficient for single motherhood of any of the three poverty measures. Of course, the range of 41-44.4% of each respective actual poverty rate implies similar magnitudes of penalties. Still, this confirms we are not underestimating the single motherhood penalty with the relative measure. Ultimately, these analyses suggest that single motherhood plays a similar role for quasi-OPM and anchored child poverty as it does for relative child poverty. Of course, the scale is quite different because quasi-OPM and anchored child poverty are much lower.

<u>Appendix II.</u> Prevalences and Penalties with Alternative Definitions of Single Motherhood in the U.S. 2018.

This second column shows that measuring single motherhood as lone motherhood (i.e. no other adults or relatives in the HH) would result in a far smaller penalty for single motherhood. The third column shows that measuring single motherhood very slightly differently (see Supplementary File) as unpartnered and uncoupled single mothers results in a slightly smaller penalty that is not significantly different.

	Single Motherhood as Measured in Analyses	***Lone Motherhood (No Other Adults or Relatives in HH)***	***Unpartnered and Uncoupled Single Motherhood***
Prevalence of Single Motherhood	18.94	11.06	18.57
Penalties for Single Motherhood	8.80	4.95	8.84
95% Confidence Intervals for Penalties	(7.28-10.32)	(3.18-6.72)	(7.30-10.38)

Notes: Penalties have been multiplied by 100. All three penalties are statistically significant at .001 level.

Appendix III.

Panel A. Descriptive Statistics for All, Single Mother HHs and Non-Single Mother HHs in the U.S. 2018: Means (Standard Deviations in Parentheses).

	All HHs (N=47,124)	*Single Mother HHs (N=8,324)*	*Coupled HHs (N=35,222)*
Poverty	0.198	0.437	0.131
	(0.399)	(0.495)	(0.337)
Single Mother HH	0.189	--	--
	(0.392)		
Jobless HH	0.462	0.128	0.024
	(0.210)	(0.335)	(0.152)
Low-Educated Head	0.116	0.152	0.102
	(0.320)	(0.359)	(0.303)
Young Head (< Age 25)	0.037	0.083	0.023
	(0.189)	(0.275)	(0.149)
Age 25-34 Head	0.246	0.349	0.215
	(0.431)	(0.477)	(0.411)
Over Age 54 Head	0.079	0.048	0.085
	(0.269)	(0.213)	(0.279)
Number of Children in HH	2.400	2.364	2.433
	(1.219)	(1.231)	(1.218)
Number 65 and Older in HH	0.078	0.043	0.088
	(0.323)	(0.217)	(0.347)
High-Educated Head	0.484	0.338	0.539
	(0.500)	(0.473)	(0.498)
Multiple Earner HH	0.593	0.128	0.683
	(0.491)	(0.449)	(0.465)
Single Father HH	0.079	--	--
	(0.269)		
Black	0.129	0.152	0.085
	(0.335)	(0.453)	(0.279)
Latino	0.246	0.083	0.230
	(0.430)	(0.448)	(0.421)
Other Race	0.113	0.089	0.123
	(0.317)	(0.284)	(0.329)

Note: All HHs is more than the sum of single mother and coupled HHs.

Panel B. Coefficients and Average Marginal Effects for All Variables in U.S. 2018 Model (N=47,124).

	Coefficient	*Z-Score*	*Average Marginal Effect (AME)*	*Z-Score*
Model With Additional Controls (i.e. Model for U.S.-Only)				
Single Mother HH	0.800***	(12.45)	0.088***	(11.35)
Jobless HH	2.729***	(21.95)	0.492***	(26.18)
Low-Educated Head	0.863***	(11.46)	0.122***	(10.72)
Young Head (< Age 25)	0.894***	(7.50)	0.101***	(6.68)
Age 25-34 Head	0.327***	(5.18)	0.034***	(5.04)
Over Age 54 Head	-0.156	(-1.43)	-0.015	(-1.46)
Number of Children in HH	0.226***	(8.61)	0.023***	(8.43)
Number 65 and Older in HH	-0.164	(-1.75)	-0.016	(-1.76)
High-Educated Head	-1.174***	(-17.66)	-0.114***	(-18.48)
Multiple Earner HH	-1.730***	(-28.51)	-0.194***	(-29.26)
Single Father HH	0.377**	(4.38)	0.038***	(4.15)

Black	0.739***	(8.74)	0.075***	(8.08)
Latino	0.797***	(12.19)	0.082***	(11.68)
Other Race	0.515***	(5.75)	0.050***	(5.44)
Model Without Additional Controls (i.e. Model for Cross-National Comparison)				
Single Mother HH	0.843***	(14.05)	0.097***	(12.65)
Jobless HH	2.661***	(21.20)	0.493***	(25.76)
Low-Educated Head	1.031***	(13.91)	0.157***	(13.03)
Young Head (< Age 25)	0.931***	(7.65)	0.108***	(6.74)
Age 25-34 Head	0.352***	(5.63)	0.037***	(5.45)
Over Age 54 Head	-0.174	(-1.59)	-0.017	(-1.64)
Number of Children in HH	0.225***	(8.54)	0.023***	(8.38)
Number 65 and Older in HH	-0.147	(-1.59)	-0.015	(-1.58)
High-Educated Head	-1.305***	(-20.23)	-0.128***	(-21.09)
Multiple Earner HH	-1.736***	(-21.20)	-0.199***	(-29.52)

Notes: HH=household. While Brady et al (2017) show penalties as both coefficients from linear probability models and AME's from logistic regression models, they favor coefficients from linear probability models because AMEs are not concordant in counterfactual simulations of penalties. As we only estimate counterfactual prevalences, we report penalties as AMEs. Coefficients from linear probability models are consistent and available upon request.
$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

<u>Appendix IV.</u> Alternative Penalties and Simulations Based on Adjusting for Immigrant-Origin and Non-Citizen Status of Lead Earner in HH.

Unfortunately, immigration and citizenship are not available in all years of U.S. data. In order to specify the U.S. models identically over time, we do not include the immigration/citizenship controls in the main analyses. The second column shows the penalty for single motherhood would be modestly larger but not substantially different than the penalty estimated when omitting those controls (i.e. the CIs for penalties overlap). Moreover, the counterfactual simulations are not meaningfully different when we control for immigrant citizen and immigrant non-citizen heads (cf. columns 1 and 2). The last two columns show the single motherhood penalties for Latinos when we do not and do control for immigration and citizenship. Again, the penalties are only modestly and not significantly different with these controls. Also, the counterfactual simulations are very similar.

	Full Sample (Table 1)	***Full Sample Adjusting for Immigrant Head and Non-Citizen Head***	***Latino Subsample (Table 2)***	***Latino Subsample Adjusting for Immigrant Head and Non-Citizen Head***
Penalties for Single Motherhood	8.80	9.58	9.20	10.24
95% Confidence Intervals for Penalties	(7.28-10.32)	(8.03-11.11)	(5.86-12.54)	(6.89-13.59)
		Child Poverty Rates		
Model Predicted	19.84	19.84	31.04	31.04
Cross-National Median Single Motherhood Prevalence	19.54	18.41	30.15	30.05
1970 U.S. Single Motherhood Prevalence	19.26	18.02	29.81	29.67
Zero Single Motherhood	17.55	16.99	28.89	28.65

Notes: Penalties have been multiplied by 100. All three penalties are statistically significant at .001 level.

Appendix V. Replication of Table 1 Using Random Reassignment Simulation: Child Poverty Rates with Predicted, and Simulations Based on Counterfactual Prevalences of Single Motherhood in the U.S. 2018.

This alternative approach randomly reassigns children from single-mother HHs to married-couple HHs until reaching a given counterfactual prevalence (see Supplementary File for code). We then predict the probability of child poverty with this lower prevalence of single motherhood. This alternative simulation approach resulted in slightly smaller reductions in child poverty. Therefore, we present the first approach in the main analyses to be more conservative for our conclusions (i.e. to show single motherhood having a slightly larger impact). Nevertheless, all conclusions are very similar with either approach.

	Regression-Based (Appendix III)		***Random Reassignment***	
	Rate (95% CIs)	***Rank (1=highest)***	***Rate (95% CIs)***	***Rank (1=highest)***
Model Predicted	19.84 (19.31, 20.37)	4th	19.84 (19.31, 20.37)	4th
Cross-National Median Prevalence	18.70 (18.13, 19.27)	4th	19.11 (18.57, 19.65)	4th
1970 Prevalence	18.37 (17.79, 18.96)	4th	18.65 (18.10, 19.21)	4th
Zero Prevalence	17.55 (16.92, 18.18)	4th	17.55 (16.92, 18.18)	4th

Note: The CIs for Regression-based and random reassignment simulations always overlap. All simulated values are significantly different from model predicted child poverty rate. Models are displayed in Appendix III.

Appendix VI. Single Motherhood Penalties with Panel Models of the PSID-CNEF.

We use the Panel Study of Income Dynamics (PSID) and the Cross-National Equivalent File (CNEF). The CNEF, which is a supplement to the PSID, provides high quality standardized measures of income incorporating taxes, tax credits, and transfers **(**Frick, Joachim R., Stephen P. Jenkins, Dean R. Lillard, Oliver Lipps, and Mark Wooden. 2007. "The Cross-National Equivalent File (CNEF) and its Member Country Household Panel Studies." *Schmollers Jahrbuch* 127: 627-654**)**. The PSID is the longest running panel in the U.S., with survey waves administered annually 1968-1993 and biannually thereafter. With weights, the demographic and economic characteristics of the PSID have been shown to be quite similar to the March Current Population Survey (CPS-ASEC) dataset used through the LIS in the paper. Our sample begins in 1997 because the PSID became biannual after 1997 and the PSID offers a standardized population weight (wght01_im) that is available only since 1997. This is also justified because the LIS analyses show that the prevalences and penalties of single motherhood were fairly stable during that period. Our sample ends in 2019 as that is the latest CNEF year available, this period corresponds with the LIS analyses in the main text, and because of COVID.

With this data, we find child poverty rates similar to the LIS. Across 1997-2019, the PSID-CNEF estimates a child poverty rate of 23.41%. The models include all four risks and the same controls as in Appendix III for the U.S. in 2018 LIS data. Below, like the main Tables, we report the single motherhood penalties multiplied by 100 for easier interpretation. The numbers in parentheses are t-scores (not multiplied by 100). All models include the aforementioned population weight and cluster standard errors by household-wave. We estimate and report several different panel techniques.

First, we estimate two-way fixed effects linear probability models of child poverty with fixed effects for each child and survey wave/year (Stata command <reghdfe>). This within-person two-way fixed effects estimator is plausibly closer to causally identified effects because they remove most stable factors with stable effects on single motherhood and child poverty. We purposefully choose fixed effects linear probability models instead of fixed effects logit models. Fixed effects logit models drop children who were always or never poor. This would drop about 54% of the sample of child-years. Moreover, children who shift into or out of single mother households but do not experience a change in poverty should certainly influence the estimates of the penalties. Therefore, we do not report fixed effects logit models (but did estimate them, and the AME's are similar to these coefficients and available upon request). The two-way FE models include 76,446 child-years across 15,070 children.

Next, we estimated fixed effects individual slopes models, which include fixed effects and unique linear time slopes for each child (Stata command <xtfeis>). These models include 71,542 child-years across 12,618 children.

Fourth, we estimate and report the difference-in-difference estimator developed by Chaise-Martin and d'Haultfoeuille (see *American Economic Review* 2020, 110: 2964-2996) (Stata command <did_multiplegt>). This new estimator addresses potential treatment effect heterogeneity and negative weights that can arise with staggered rollouts of treatments in traditional two-way fixed effects and difference-in-difference estimators. We estimated the model omitting or including dynamic effects, which did not change the results meaningfully. So, here we report the estimate without dynamic effects.

Fifth, we follow Jakiela's (2021, see https://pjakiela.github.io/TWFE/TWFE-2021-03-24.pdf) strategy for identifying and removing cases that would have negative weights in two-way

FE models. We get the "residualized treatment" from a regression of single motherhood on the person and wave FEs. We then reestimate the model while dropping cases with below mean (i.e. negative) residualized treatments (i.e., those vulnerable to negative weights). The coefficient for single motherhood becomes negatively signed, has a trivial magnitude, and becomes statistically insignificant.

In sum, all analyses here show much smaller penalties with these arguably more causally identified estimates. Given the penalties influence the simulations, these much smaller penalties imply much smaller reductions in child poverty with lower prevalences of single motherhood.

Estimates of Single Motherhood Penalties with Alternative Panel Modeling Strategies in PSID-CNEF Data, 1997-2019: Coefficients and T-Scores in Parentheses.

	Appendix III for Comparison	*Two-Way FEs*	*Fixed Effects Individual Slopes*	*Chaise-Martin & D'Haultfœuille*	*Jakiela Strategy: Two-Way FEs After Dropping Negative Weights*
Single Mother HH	8.80 (11.43)	4.49 (8.53)	5.09 (14.64)	2.40 (3.48)	-0.16 (-0.05)

Appendix VII. Cross-National Variation in the Risks of Child Poverty Based on Analyses with Recent LIS Data.

Panel A: Prevalences of Risks				
	Single Motherhood	Jobless	Low Education	Young Headship
Min	4.63	1.07	5.18	0.54
Median	14.73	4.80	13.89	1.99
Max	24.75	11.62	36.60	3.71
Coefficient of Variation	0.39	0.49	0.48	0.48
USA	18.94	4.62	11.58	3.71
USA Rank ***(1st=highest)***	12th	17th	20th	1st

Panel B: Penalties for Risks				
	Single Motherhood	Jobless	Low Education	Young Headship
Min	-3.71	4.62	-2.97	-1.00
Median	1.54	39.83	4.63	9.57
Max	9.67	65.05	19.98	34.47
Coefficient of Variation	2.02	0.37	0.90	0.70
# of Countries Penalty NOT Significantly Positive?	24	2	14	18
USA	9.67	49.22	15.66	10.83
USA Rank ***(1st=highest)***	1st	7th	4th	11th

Note: USA penalties based on same model specification as other rich democracies (i.e. omitting race/ethnicity and single fatherhood, see Appendix III). All U.S. penalties are significantly positive. Also see Figures 2-3.

Appendix VIII. Racial Decomposition for **Native American and Asian** Children of Prevalences and Penalties of Single Motherhood, and Predicted Child Poverty with Simulations Based on Counterfactual Prevalences of Single Motherhood in the U.S. 2018.

	White Children	***Native American Children***	***Asian Children***
Prevalence of Single Motherhood (%)	12.72	25.54	8.14
Penalties for Single Motherhood (%)	8.92	8.14	7.74
N	26234	635	2519

	White Child Poverty (%)	***Native American Child Poverty (%)***	***Native American - White Ratio***	***Asian Child Poverty (%)***	***Asian-White Ratio***
Actual	11.42	31.02	2.72	13.42	1.18
Model Predicted	11.42	31.02	2.72	13.42	1.18
Cross-National Median Single Motherhood Prevalence	10.75	29.83	2.77	13.42	1.25
1970 U.S. Single Motherhood Prevalence	10.46	29.52	2.82	13.15	1.26
Zero Single Motherhood	9.71	28.71	2.96	12.46	1.28

Notes: The single motherhood penalty for Native American children is not statistically significant (z=0.98), partly due to the small N. The single motherhood penalty for Asian children is statistically significant (z=2.50).

Appendix IX. Alternative Estimates of Penalties for Single Motherhood, and Predicted Child Poverty with Simulations Based on Counterfactual Prevalences of Single Motherhood in the U.S. 2018 (N=47,124).

	Appendix III	*No Other Independent Variables Except Single Motherhood*	*Omitting Education, Employment and Age But Including Other Controls*	*Controlling for Employment Intensity Per Working-Age Adult*
Penalties for Single Motherhood	8.80 (7.28-10.32)	29.38 (27.34-31.42)	24.83 (22.80-26.86)	10.11 (8.63-11.60)
		Child Poverty Rates		
Model Predicted	19.84	19.84	19.84	19.84
Cross-National Median Single Motherhood Prevalence	18.70	17.26	17.35	18.44
1970 U.S. Single Motherhood Prevalence	18.37	16.39	16.53	18.07
Zero Single Motherhood	17.55	14.28	14.52	17.12

Notes: The numbers in parentheses are 95% confidence intervals. Penalties have been multiplied by 100. All three penalties are statistically significant at .001 level.

Appendix X. Advances Beyond and Comparisons With Prior Similar Studies.

Because of word count limits, we do not have space to precisely document all of the specific ways the present analysis advances beyond prior similar studies. We emphasize our analyses directly build upon and are genuinely inspired by prior comparative studies on child poverty. Nevertheless, we advance the field by incorporating a variety of specific improvements over prior comparative studies on child poverty cited in the text (e.g. Gornick and Jäntti, Chen and Corak, and Heuveline and Weinshenker).

In terms of substantive advance, we make four points. First, none of the prior comparative studies incorporates race/ethnicity or racial inequality. Of course, this is understandable given these studies' strictly cross-national approach forces omission of race/ethnicity variables.

Second, the PP framework explicitly names, describes and compares "prevalences" and "penalties" that are implicitly estimated in prior decompositions. In addition to the present analysis being different from prior comparative studies, this distinguishes the present analysis from Baker and colleagues' study of racial inequalities in overall (not child) poverty (2022).

Third, relatedly, the PP framework uses simulations to predict how much U.S. poverty would change under counterfactual prevalences. Probably the closest example would Gornick and Jäntti's predictions of *other countries' poverty* with U.S. prevalences or penalties (see their Table 4). This is similar but reverses the simulations. This means prior studies have not addressed our focus of how U.S. poverty would be different with counterfactual prevalences.

Fourth, past research could be read as more equivocal about the impact of single motherhood. While Heuveline and Weinshenker were more skeptical about family structure's role, Chen and Corak were more ambivalent, and Gornick and Jäntti perhaps conclude that family structure remains important. For instance, Gornick and Jäntti write: "family structure still matters a great deal" (p.563) and "in nearly all of our study countries. . .children who live with single parents are more likely to be poor than are children who live with two parents" (p.567). On balance, Gornick and Jäntti concurred with the others that family structure cannot explain cross-national variation. Nevertheless, our evidence that the single mother penalty is not significant in 24 of 30 rich democracies seems somewhat different with Gornick and Jäntti's conclusions. Finally, our finding that the single mother penalty is always the smallest penalty of the four risks is novel for this particular comparative literature.

In terms of analytical advance, we make four points. First, none analyzes a long period of U.S. history, as many countries, or as recent years. Chen and Corak compare how 12 countries change ~1991-2000; Gornick and Jäntti analyze a cross-section of 14 rich democracies ~2004; Heuveline and Weinshenker analyze a cross-section of 15 countries ~2000. By contrast, we examine 30 rich democracies and 41 U.S. datasets over 1979-2019.

Second, prior studies combine "family structure" effects into a more comprehensive category. To be specific, prior decompositions tend to combine the number of children and other family structures besides single motherhood and coupled HHs into one category of factors. By contrast, we concentrate exclusively and precisely on the role of single motherhood. This provides a cleaner interpretation of how much America's child poverty owes to single motherhood alone.

Third, we incorporate a more comprehensive set of predictors of poverty. Partly, this is a result of advances in LIS data since those studies have been published. Partly, this is a result of us estimating U.S.-specific models that include more controls.

Fourth, these studies focus more on unconditional differences in poverty between single mother and coupled HHs. Instead, we advocate for comparisons of conditional penalties.

The text is more explicit about how the present analysis differs from prior U.S.-specific studies. We summarize several of the main advances here. Compared to prior U.S.-specific studies, we feature: (a) more valid and reliable income and poverty measures; (b) a comparison with all four major risks; (c) more complete model specifications; (d) multiple definitions of single motherhood; (e) a much longer and more recent time period; and (f) a more comprehensive set of tests.

<u>Appendix XI.</u> Comparisons of Poverty in Post-Fisc Equivalized Income Versus Market Income, and Minus Public Transfers or Private Transfers.

This Appendix includes additional cross-national, over time, and across race/ethnicity analyses. First, we analyze "market income" (i.e. LIS variable "hifactor"). This is the closest feasible indicator to earnings as this is overwhelmingly labor income like earnings (especially in households with children and single-mother households). Further, the LIS variables for wage income ["hi11"] and ["hi12"] are not as standardized and consistently available across countries. Second, we calculate post-fisc income minus "public transfers" (i.e. the LIS variable "hitransfer" minus private transfers ["hiprivate"] and private pensions ["hi33"]). Third, we calculate post-fisc income minus alimony and child support. Then, we define poverty in terms of the same threshold but for (i) market income, (ii) post-fisc income minus public transfers, and (iii) post-fisc income minus private transfers. Fourth, to break down transfers, we can also compare a few different aggregated categories within public transfers. Fifth, we added a new analysis where we do a side-by-side comparison of the predictors of child poverty in 2018 and in 2021 during the expanded child tax credit (CTC). This underlines the role of generous transfers in reducing the level of child poverty and the penalties attached to risks. We hope the editor and R1 can sympathize this produces a huge quantity of new information. In turn, we are forced to distill this information succinctly in the text but answer the questions directly here.

Panel A. Details on Pre-Fisc and Post-Fisc Poverty and Reductions to Attributable to Specific Income Components in 2018.

This panel uses the traditional approach of calculating the % reduction estimating the rate of change between various pre-fisc and post-fisc poverty rates in 2018. This approach removes total or some variant of taxes and transfers from post-fisc income and then and recalculates poverty. This simulates what poverty would be in the absence of taxes and transfers. The rate of change between those two poverty rates allows the calculation of how much taxes and transfers reduce poverty. For instance, the far right column removes alimony and child support from income (i.e. certain kinds of private transfers) and this allows us to show how much alimony and child support reduce poverty – by contrasting what the poverty rate would be in the absence of alimony and child support. Market poverty excludes all public taxes and transfers.

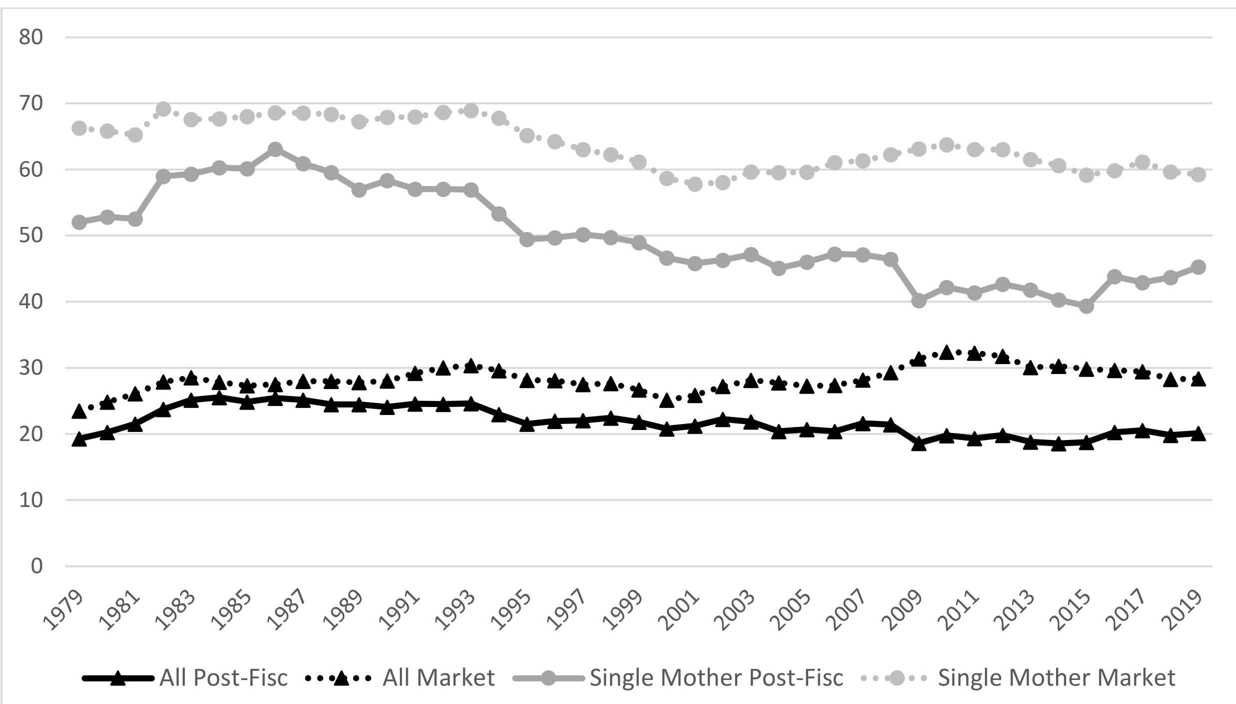
In short, Panel A shows America's high child poverty is principally driven by its lower poverty reduction via taxes and transfers. The U.S. is closer to the middle of the distribution in market poverty than in post-fisc poverty. , and the U.S. is cross-nationally ranked quite low in each component of taxes and transfers. On balance, single mother HHs are still 7th highest in terms of market poverty – so they certainly are disadvantaged in the labor market as well. Yet, it seems their comparative disadvantage is even more pronounced in taxes and transfers.

			% Reduction Due to:				
	Post-Fisc Poverty	***Market Poverty***	***Taxes & Transfers***	***Transfers***	***Family Benefits***	***Unemployment Benefits***	***Alimony & Child Support***
All Children							
U.S. 2018	19.84%	28.29%	29.88%	36.46%	26.38%	0.77%	3.39%
U.S. Ranking (1=highest)	4th	10th	25th	27th	25th	27th	19th

Cross-National Median	10.76%	21.31	45.18%	56.54%	43.97%	10.82%	6.27%
Children in Single Mother HHs							
U.S. 2018	43.66%	59.65%	26.82%	28.96%	20.9654	0.28%	6.47%
U.S. Ranking (1=highest)	1st	7th	26th	27th	22nd	25th	20th
Cross-National Median	26.30%	46.5%	49.71%	48.95%	39.05%	7.84%	15.05%

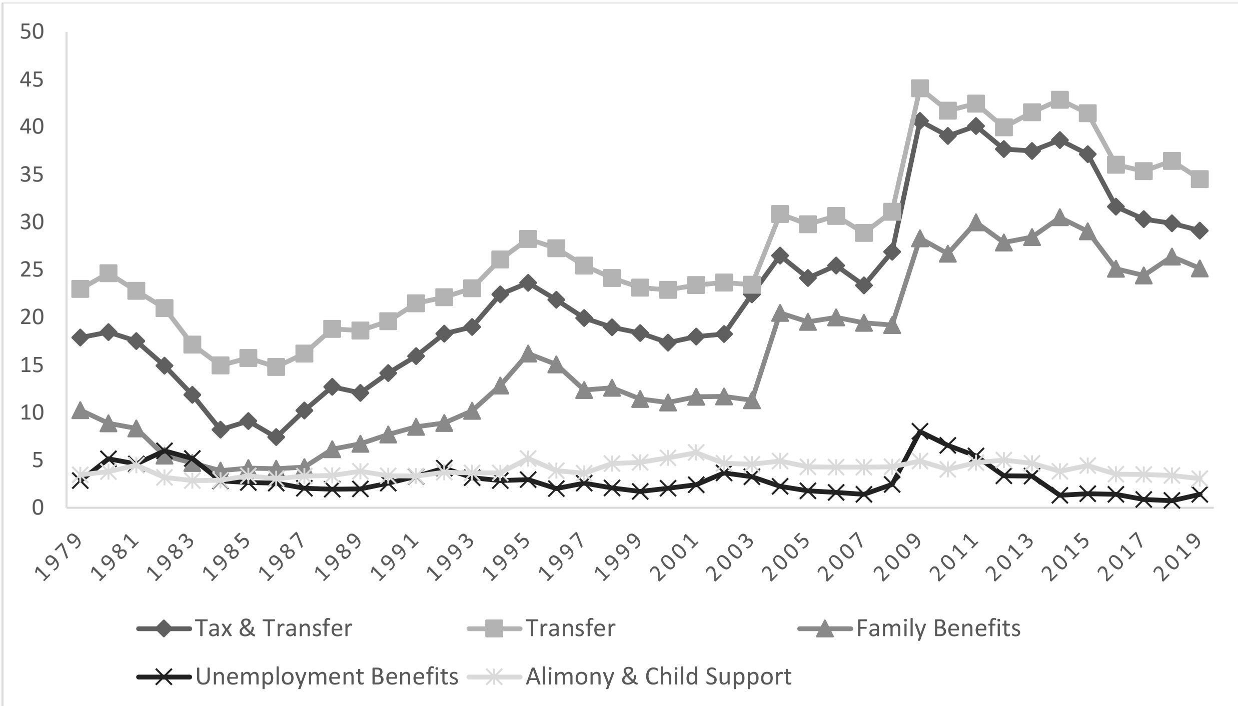
Panel B. Child Post-Fisc and Pre-Fisc Poverty Trends for All and Single Mother HHs.

This panel extends Panel A to show the trends in two poverty rates for all children and children in single mother households over time 1979-2019. Post-fisc poverty includes all taxes and transfers. "Market" poverty removes all taxes and transfers. As this figure shows, there has been a modest decline in post-fisc child poverty (especially among single mother HHs). However, the decline is less pronounced in market poverty. As a result, the decline in child poverty has principally been driven by increasing taxes and transfers.



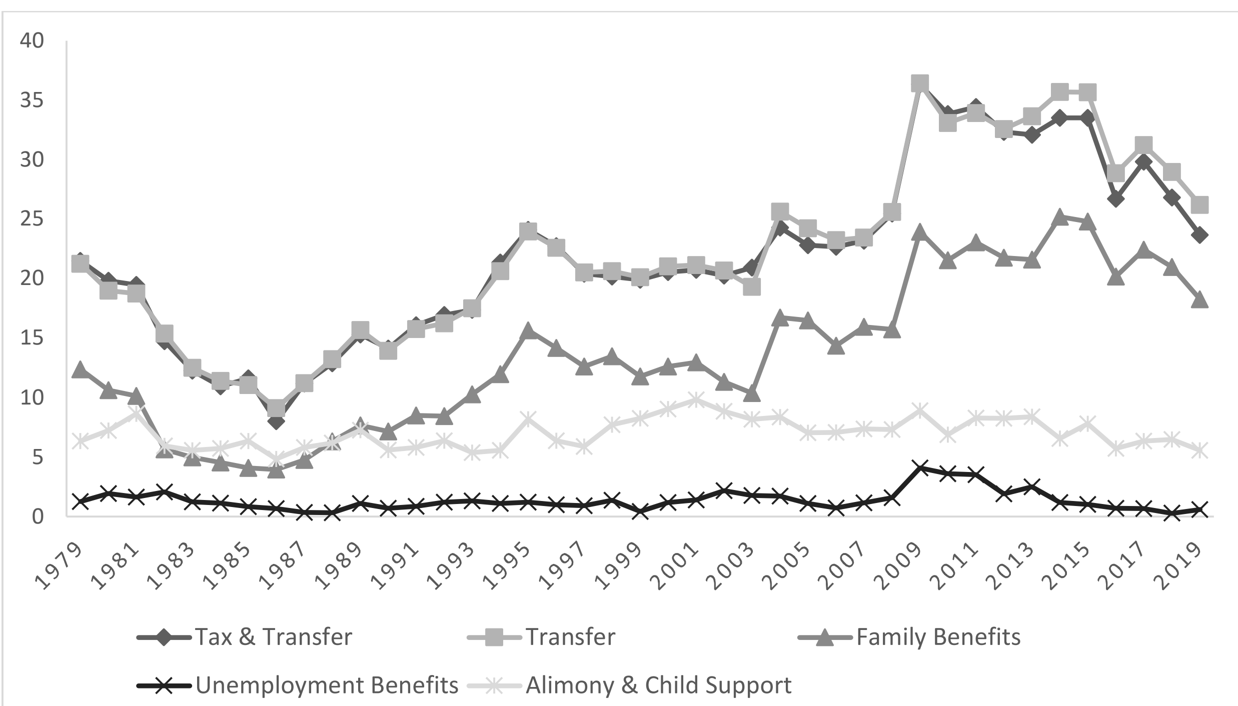
Panel C. % Reduction in Poverty Due to Various Income Components for All Children

This panel extends Panel A and shows the percent reductions attributable to each component over time 1979-2019. This panel is similar to Panel D, which shows only children in single mother HHs. However, this Figure is confined to ALL children and is not specifically focused on children in single mother HHs.



Panel D. % Reduction in Poverty Due to Various Income Components for Children in Single Mother HHs.

This panel extends Panel A and shows the percent reductions attributable to each component over time 1979-2019. This figure is similar to Panel C, which shows all children. However, this Figure is confined specifically to ONLY children in single mother HHs.



Panel E. Poverty Reduction Due to Various Income Components Broken Down by Ethno-Racial Groups.

This Panel is similar to Panel A, except it decomposes items by race/ethnicity. Black and Latino children appear to be disadvantaged in nearly every component of household income and transfers. There does not appear to be an obvious "primary" source of the racial inequalities in child poverty because the disparities exist in both market income and in most taxes and transfers. On balance, Black children appear to benefit slightly more than white children in family benefits and "other race" children appear to benefit more than white children in unemployment benefits.

			% Reduction Due to:				
	Post-Fisc Poverty	***Market Poverty***	***Taxes & Transfers***	***Transfers***	***Family Benefits***	***Unemployment Benefits***	***Alimony & Child Support***
All Children							
white	11.42%	18.11%	36.95%	43.27%	30.90%	0.70%	4.70%
Black	34.85%	48.61%	28.30%	32.29%	24.01%	0.96%	3.15%
Latino	31.04%	41.08%	24.44%	32.67%	24.68%	0.66%	2.36%
Other	16.58%	23.52%	29.50%	36.52%	23.50%	0.95%	4.03%
Children in Single Mother HHs							
white	33.68%	49.25%	31.62%	32.50%	21.83%	0.37%	10.25%
Black	51.98%	70.52%	26.29%	28.30%	22.28%	0.15%	4.28%
Latino	48.01%	62.65%	23.38%	27.04%	19.68%	0.24%	5.18%
Other	41.61%	55.23%	24.66%	26.67%	17.20%	0.68%	7.38%

Panel F. Average Marginal Effects and (Z-Scores) for Logit Model of Child Poverty in 2018 and 2021 in U.S.

This panel models of poverty in 2018 and 2021. The model for 2018 is identical to the model shown in the paper and appendices above. The model for 2021 is not part of the main analysis as the main analysis ends in 2019 before COVID. However, this side by side comparison of 2018 and 2021 shows how the coefficients for predictors of poverty changed especially under the expanded Child Tax Credit in 2021.

	2018 (N=47,124)	***2021 (N=38,547)***
Single Mother HH	0.088***	0.042***
	(11.35)	(6.22)
Jobless HH	0.492***	0.463***
	(26.18)	(17.98)
Low-Educated Head	0.122***	0.065***
	(10.72)	(5.59)
Young Head (< Age 25)	0.101***	0.118***
	(6.68)	(8.06)
Age 25-34 Head	0.034***	0.170**
	(5.04)	(2.73)
Over Age 54 Head	-0.015	0.019*
	(-1.46)	(2.03)

Number of Children in HH	0.023***	-0.009**
	(8.43)	(-3.00)
Number 65 and Older in HH	-0.016	-0.028**
	(-1.76)	(-3.20)
High-Educated Head	-0.114***	-0.077***
	(-18.48)	(-14.25)
Multiple Earner HH	-0.194***	-0.135***
	(-29.26)	(-23.46)
Single Father HH	0.038***	0.021*
	(4.15)	(2.44)
Black	0.075***	0.032***
	(8.08)	(3.80)
Latino	0.082***	0.037***
	(11.68)	(6.02)
Other Race	0.050***	0.031**
	(5.44)	(3.46)

SUPPLEMENTARY FILE: Code for LIS Dataset Construction and Analyses.
*Analyses conducted November 2023 – January 2024 using LISSY
*The following code can be submitted to the LISSY interface of the Luxembourg Income Study (www.lisdatacenter.org) by registered users.
*For "[user]" we substitute one author's name of her/his storage folder in LISSY
*The code is organized mostly in sequence of paper in terms of figures, Table 1, and then appendices.

```
** Loop for creating the country files and merging them
**include all most recent datasets on November 24, 2023 - plus all US datasets 1979-2019**
**Use USA 2018 instead of 2019 (which was collected March 2020)
**Use Slovenia 2012 because 2015 lacks number of children**

global c "au18 at19 be17 ca19 cz16 dk16 ee16 fi16 fr18 de19 gr16 hu15 ie19 il18 it16 is10 jp13 lt18 lu19 nl18 no19 pl19 sk18
si12 es19 se19 ch18 tw16 uk19 us79 us80 us81 us82 us83 us84 us85 us86 us87 us88 us89 us90 us91 us92 us93 us94 us95 us96
us97 us98 us99 us00 us01 us02 us03 us04 us05 us06 us07 us08 us09 us10 us11 us12 us13 us14 us15 us16 us17 us18 us19 us21"

foreach x of global c {
*HH file
use $`x'h, clear

*drop missing
drop if dhi==.
drop if dhi==0
drop if hwgt==.
drop if hwgt==0

*equivalize and top and bottom-code income
gen wt=hwgt*nhhmem
gen ey=dhi/(sqrt(nhhmem))
qui sum ey [w=wt]
gen botlin=0.01*_result(3)
replace ey=botlin if ey<botlin
quietly sum dhi [w=wt], de
gen toplin=10*_result(10)
replace ey=(toplin/(nhhmem^0.5)) if dhi>toplin

*Poverty thresholds
quietly sum ey [w=wt], de
generate povl4=_result(10)*.4
generate povl5=_result(10)*.5
generate povl6=_result(10)*.6

*Define poverty
gen poor5=.
replace poor5=0 if ey>= povl5 & ey!=.
replace poor5=1 if ey< povl5 & ey!=.

*HH employment variables
gen multearn=.
replace multearn=0 if nearn==0 | nearn==1
replace multearn=1 if nearn>1 & nearn!=.

gen unemphh=.
replace unemphh=0 if nearn>0 & nearn!=.
replace unemphh=1 if nearn==0

*combined employment variable
recode nearn (0 = 0 "Unemp HH") (1 = 1 "One Earn") (2/max = 2 "Multi Earn"), gen(emphh)

sort hid
keep hid did year dname cname hwgt hhtype hpartner nhhmem nhhmem65 nhhmem17 nearn ey dhi hitotal hifactor hitransfer
hi33 hiprivate poor5 unemphh multearn emphh povl5 hi521 hipension hi41 hi42 hipubsoc
```

```
save $mydata/[user]/`x'h, replace

*Person File
use $`x'p, clear

*Head and Sex for single parent variables later*
gen head=.
replace head=1 if relation==1000
replace head=0 if relation>1000 & relation!=.

recode sex (1=0)(2=1)(.=.), gen(female)
recode sex (1=1)(2=0)(.=.), gen(male)

sort hid
keep hid pid did year relation partner parents nchildren ageyoch age sex marital immigr citizen yrsresid ethnic_c immigr_c educ
educ_c emp head male female pilabour pi11 hourstot weeks
save $mydata/[user]/`x'p, replace

merge m:1 hid using $mydata/[user]/`x'h, keep(match) nogen

*create variable for lead earner*
replace pilabour = pi11 if pilabour<0
egen double maxinc=max(pilabour) if pilabour!=., by(hid)
gen lead=pilabour==maxinc
egen maxage=max(age) if lead & age!=., by(hid)
replace lead=0 if age!=maxage
egen numlead = sum(lead), by(hid)
gen rlead = runiform()
egen maxrlead = max(rlead) if lead, by(hid)
replace lead = 0 if numlead>1 & rlead<maxrlead

*create variables for education*
gen leadeduc_a=educ*lead
egen leadeduc=max(leadeduc_a), by(hid)
recode leadeduc (3=1) (nonmiss=0), gen(highed)
recode leadeduc (1=1)(nonmiss=0), gen(lowed)

*create age of head variables
gen agelead_a=age*lead
egen agelead=max(agelead_a), by(hid)

gen leadu25=0 if agelead!=.
replace leadu25=1 if agelead<25 & agelead!=.

gen lead2534=0 if agelead!=.
replace lead2534=1 if agelead>24 & agelead<35

gen leado54=0 if agelead!=.
replace leado54=1 if agelead>54 & agelead!=.

*create family structure variables*
gen married=.
replace married=0 if marital>=200 & marital!=.
replace married=1 if marital<200 | partner==110

gen marriedhh_a=married*head
egen marriedhh=max(marriedhh_a), by(hid)
recode marriedhh (1=0)(0=1)(.=.), gen(single)

recode nchildren 2/17=1, gen(nchild)
replace nchild=0 if ageyoch>17 & ageyoch!=.
```

```
gen sing_mom_a=head*female
gen sing_mom_b=sing_mom_a*single
gen sing_mom_c=sing_mom_b*nchild

egen singmom=max(sing_mom_c), by(hid)
replace singmom=1 if singmom>1 & singmom!=.

gen sing_dad_a=head*male
gen sing_dad_b=sing_dad_a*single
gen sing_dad_c=sing_dad_b*nhhmem17
egen singdad =max(sing_dad_c), by(hid)
replace singdad=1 if singdad>1

gen fhnk_a=0
replace fhnk_a=1 if sing_mom_b ==1 & nhhmem17==0
egen fhnk=max(fhnk_a), by(hid)

gen mhnk_a=0
replace mhnk_a=1 if sing_dad_b ==1 & nhhmem17==0
egen mhnk=max(mhnk_a), by(hid)

*combined lead age categorical variable
recode agelead (min/24 = 1) (25/34 = 2) (35/54 = 3) (55/max = 4), gen(agecat)
label define agelab 1 "Under 25" 2 "a2534" 3 "a3554" 4 "a55plus, replace
label val agecat agelab

*combined education variable
gen educhh=1 if lowed==1
replace educhh=2 if lowed==0 & highed==0
replace educhh=3 if highed==1

*combined family variable
gen famHH = 1
replace famHH = 2 if singmom==1
replace famHH = 3 if singdad==1
label define famlab 1 "Couple" 2 "Single Mom" 3 "Single Dad", replace
label val famHH famlab

save $mydata/[user]/`x', replace
}

*** append country files
global c "at19 be17 ca19 cz16 dk16 ee16 fi16 fr18 de19 gr16 hu15 ie19 il18 it16 is10 jp13 lt18 lu19 nl18 no19 pl19 sk18 si12
es19 se19 ch18 tw16 uk19 us79 us80 us81 us82 us83 us84 us85 us86 us87 us88 us89 us90 us91 us92 us93 us94 us95 us96 us97
us98 us99 us00 us01 us02 us03 us04 us05 us06 us07 us08 us09 us10 us11 us12 us13 us14 us15 us16 us17 us18 us19 us21"

use $mydata/[user]/au18, clear
foreach x of global c {
append using "$mydata/[user]/`x'"
}

tabstat did, by(dname)

save $mydata/[user]/kidprevpen2024, replace
```

<u>Estimates for Figures 1-2, 4-5 and Appendix VII*</u>**

```
use $mydata/[user]/kidprevpen2024, clear

// listwise deletion
drop if age>=18 | poor5>=. | famHH>=. | educhh>=. | agelead>=. | unemphh>=.
// dname
```

```
encode dname, gen(dname2)
// unique HH id
gen hid2 = 1000*hid + did
// looping over variables
foreach x in poor5 singmom unemphh lowed leadu25 {
		proportion `x' [pw = hwgt], over(dname2) vce(cluster hid2)
}

**Estimates for Figure 3, 4 & 5 and Appendix VII*
// listwise deletion
drop if age>=18 | poor5>=. | famHH>=. | educhh>=. | agelead>=. | unemphh>=.

// unique HH id
gen hid2 = 1000*hid + did

// looping through countries
levelsof dname, local(countries)
foreach i of local countries {
		di "--------------"
		di "COUNTRY = `i'"
		// logit model
		logit poor5 b1.emphh b2.educhh b3.agecat i.singmom nhhmem17 nhhmem65 if dname=="`i'" [pw=hwgt], cluster(hid2)
		// marginal effects
		margins, dydx(singmom educhh emphh agecat) post
		estimates store `i'
		di "--------------"
}

**Estimates for Figure 4 and Appendix III*
*Select US Datasets Only 1979-2019 and Code Race/Ethnicity
keep if did==6 | did==835 | did==836 | did==837 | did==838 | did==839 | did==840 | did==15 | did==841 | did==842 | did==843 |
did==844 | did==45 | did==528 | did==527 | did==66 | did==526 | did==525 | did==85 | did==524 | did==523 | did==107 |
did==522 | did==521 | did==520 | did==172 | did==519 | did==518 | did==228 | did==517 | did==516 | did==229 | did==515 |
did==514 | did==300 | did==513 | did==512 | did==393 | did==511 | did==510 | did==685

tab dname

*1979-1986 race coding available
recode ethnic_c (11 = 1 "White") (21 = 2 "Black") (12 22 92 = 3 "Latino") (91 = 4 "Other") if year<1987, gen(race)

*1987, new race coding available
replace race=1 if ethnic_c==1 & year>1986
replace race=2 if ethnic_c==3 & year>1986
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10| ethnic_c==12) & year>1986
replace race=4 if (ethnic_c==5| ethnic_c==7| ethnic_c==9| ethnic_c==11) & year>1986

// listwise deletion
drop if age>=18 | poor5>=. | famHH>=. | educhh>=. | agelead>=. | unemphh>=.

// unique HH id
gen hid2 = 1000*hid + did

// looping through countries
levelsof dname, local(countries)

foreach i of local countries {
		di "--------------"
		di "COUNTRY = `i'"
		// logit model
		logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if dname=="`i'" [pw=hwgt],
cluster(hid2)
		// marginal effects
```

```
		margins, dydx(famHH educhh emphh agecat) post
		estimates store `i'
		di "--------------"
}

**Descriptives in Appendix III*
tabstat poor5 unemphh lowed leadu25 lead2534 leado54 nhhmem17 nhhmem65 highed multearn singdad black latino other if
age<18 [w=hwgt], stats (mean sd n)

tabstat poor5 unemphh lowed leadu25 lead2534 leado54 nhhmem17 nhhmem65 highed multearn black latino other if age<18 &
singdad==0 [w=hwgt], by(singmom) stats (mean sd n)

**Estimates for Figure 6*
keep if did==510

gen race=.
replace race=1 if ethnic_c==1
replace race=2 if ethnic_c==3
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10| ethnic_c==12)
replace race=4 if (ethnic_c==5| ethnic_c==7| ethnic_c==9| ethnic_c==11)

gen black=0 if race!=.
replace black=1 if race==2

gen latino=0 if race!=.
replace latino=1 if race==3

gen other=0 if race!=.
replace other=1 if race==4

tabstat black latino other, stats (mean n)

**model predicted values for the US ALL controls
logit poor5 unemphh lowed leadu25 singmom lead2534 leado54 nhhmem17 nhhmem65 highed multearn singdad black latino
other if age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*-1 SD Less Single Mother Prevalence (.1891481-.05697)* .1891481
margins, at(singmom=(.13218))

*Half Single Motherhood Prevalence*
margins, at(singmom=(.09457405))

*-2 SD Less Single Mother Prevalence*
margins, at(singmom=(.0752))

*Zero Single Motherhood*
margins, at(singmom=(0))

*Cross-National Median Prevalences*
margins, at(leadu25=(.02115) singmom=(.14654) lowed=(.14149) unemphh=(.05122))

*Minus One Cross-National SD Prevalences*
margins, at(leadu25=(.02646) singmom=(.13241) lowed=(.03581) unemphh=(.01711))
```

```
*1970 Prevalences*
margins, at(leadu25=(.1023) singmom=(.106) lowed=(.3648) unemphh=(.068))

*Zero Prevalences*
margins, at(leadu25=(0) singmom=(0) lowed=(0) unemphh=(0))
```

****Estimates for Figure 7***

```
use $mydata/[user]/kidprevpen2024, clear

*Select US Datasets Only 1979-2019 and Code Race/Ethnicity
keep if did==6 | did==835 | did==836 | did==837 | did==838 | did==839 | did==840 | did==15 | did==841 | did==842 | did==843 |
did==844 | did==45 | did==528 | did==527 | did==66 | did==526 | did==525 | did==85 | did==524 | did==523 | did==107 |
did==522 | did==521 | did==520 | did==172 | did==519 | did==518 | did==228 | did==517 | did==516 | did==229 | did==515 |
did==514 | did==300 | did==513 | did==512 | did==393 | did==511 | did==510 | did==685
tab dname

*1979-1986 race coding available
recode ethnic_c (11 = 1 "White") (21 = 2 "Black") (12 22 92 = 3 "Latino") (91 = 4 "Other") if year<1987, gen(race)

*1987, new race coding available
replace race=1 if ethnic_c==1 & year>1986
replace race=2 if ethnic_c==3 & year>1986
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10| ethnic_c==12) & year>1986
replace race=4 if (ethnic_c==5| ethnic_c==7| ethnic_c==9| ethnic_c==11) & year>1986

gen black=0 if race!=.
replace black=1 if race==2

gen latino=0 if race!=.
replace latino=1 if race==3

gen other=0 if race!=.
replace other=1 if race==4

tabstat black latino other, stats (mean n) by(year)

// looping through countries
levelsof did, local(countries)
foreach i of local countries {

// estimating penalties with coefficients from AMEs from logit models
 di "did = `i'"
qui logit poor5 unemphh multearn lowed highed singmom singdad leadu25 lead2534 leado54 nhhmem17 nhhmem65 black latino
other if age<18 & did==`i' [pw=hwgt], cluster(hid)
*1970 Single Motherhood*
margins, at(singmom=(.106))
*Zero Single Motherhood*
margins, at(singmom=(0))
}
```

****Estimates for Table 1***

```
*Actual child poverty rates across race
tabstat poor5 if singmom!=. & unemphh!=. & lowed!=. & leadu25!=. & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. &
nhhmem17!=. & nhhmem65!=. & highed!=. & multearn!=. & age<18 & did==510 [w=hwgt], by(race) stats (mean semean n)

*Prevalences for White people*
tabstat unemphh lowed leadu25 singmom if poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=. &
nhhmem65!=. & highed!=. & multearn!=. & black!=1 & latino!=1 & other!=1 & age<18 & did==510 [w=hwgt], by(did) stats
(mean semean n)

*Prevalences for Black people*
```

```
tabstat unemphh lowed leadu25 singmom if poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=. &
nhhmem65!=. & highed!=. & multearn!=. & black==1 & age<18 & did==510 [w=hwgt], by(did) stats (mean semean n)

*Prevalences for Latino people*
tabstat unemphh lowed leadu25 singmom if poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=. &
nhhmem65!=. & highed!=. & multearn!=. & latino==1 & age<18 & did==510 [w=hwgt], by(did) stats (mean semean n)

*Penalties for White people*
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if black!=1 & latino!=1 & other!=1 & age<18 &
did==510 [pw=hwgt], cluster(hid)
margins, dydx(famHH emphh educhh agecat)

logit poor5 unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed multearn if black!=1 &
latino!=1 & other!=1 & age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*Zero Single Motherhood*
margins, at(singmom=(0))

*Penalties for Black people*
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if black==1 & age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH emphh educhh agecat)

logit poor5 unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed multearn if black==1 &
age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*Penalties for Latino people*
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if latino==1 & age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH emphh educhh agecat)

logit poor5 unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed multearn if latino==1 &
age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
```

```
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*Notes in text about child poverty rates in single mother and coupled households
tabstat poor5 if singmom==1 & unemphh!=. & lowed!=. & leadu25!=. & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=. & nhhmem65!=. & highed!=. & multearn!=. & age<18 & did==510 [w=hwgt], by(race) stats (mean semean n)

tabstat poor5 if marriedhh==1 & singmom!=. & unemphh!=. & lowed!=. & leadu25!=. & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=. & nhhmem65!=. & highed!=. & multearn!=. & age<18 & did==510 [w=hwgt], by(race) stats (mean semean n)
```

<u>*Code for Appendix I.</u>

```
use $mydata/[user]/kidprevpen2024, clear

*Select US Datasets Only 1979-2019
keep if did==6 | did==835 | did==836 | did==837 | did==838 | did==839 | did==840 | did==15 | did==841 | did==842 | did==843 | did==844 | did==45 | did==528 | did==527 | did==66 | did==526 | did==525 | did==85 | did==524 | did==523 | did==107 | did==522 | did==521 | did==520 | did==172 | did==519 | did==518 | did==228 | did==517 | did==516 | did==229 | did==515 | did==514 | did==300 | did==513 | did==512 | did==393 | did==511 | did==510 | did==685

gen quasiopm=0 if ey!=.
replace quasiopm=1 if ey<3696.610169 & year==1979
replace quasiopm=1 if ey<4221.290323 & year==1980
replace quasiopm=1 if ey<4624.028269 & year==1981
replace quasiopm=1 if ey<4956.818 & year==1982
replace quasiopm=1 if ey<5091.828794 & year==1983
replace quasiopm=1 if ey<5297.975709 & year==1984
replace quasiopm=1 if ey< 5498.319328 & year==1985
replace quasiopm=1 if ey< 5592.307692 & year==1986
replace quasiopm=1 if ey<5790.265487 & year==1987
replace quasiopm=1 if ey<6030.414747 & year==1988
replace quasiopm=1 if ey<6352.427 & year==1989
replace quasiopm=1 if ey<6642.64 & year==1990
replace quasiopm=1 if ey<6960.638 & year==1991
replace quasiopm=1 if ey<7150.82 & year==1992
replace quasiopm=1 if ey<7393.22 & year==1993
replace quasiopm=1 if ey<7564.162 & year==1994
replace quasiopm=1 if ey<7789.286 & year==1995
replace quasiopm=1 if ey<8028.221 & year==1996
replace quasiopm=1 if ey<8178.75 & year==1997
replace quasiopm=1 if ey<8335.032 & year==1998
replace quasiopm=1 if ey<8497.403 & year==1999
replace quasiopm=1 if ey< 8782.55 & year==2000
replace quasiopm=1 if ey< 9087.5 & year==2001
replace quasiopm=1 if ey< 9215.493 & year==2002
replace quasiopm=1 if ey< 9414.388 & year==2003
replace quasiopm=1 if ey< 9693.333 & year==2004
replace quasiopm=1 if ey< 9913.636 & year==2005
replace quasiopm=1 if ey< 10385.71 & year==2006
replace quasiopm=1 if ey< 10639.02 & year==2007
replace quasiopm=1 if ey< 11184.62 & year==2008
replace quasiopm=1 if ey< 10996.64 & year==2009
replace quasiopm=1 if ey< 11089.83 & year==2010
replace quasiopm=1 if ey< 11580.53 & year==2011
replace quasiopm=1 if ey< 11683.93 & year==2012
replace quasiopm=1 if ey< 11896.36 & year==2013
replace quasiopm=1 if ey< 12229.91 & year==2014
replace quasiopm=1 if ey< 12229.91 & year==2015
replace quasiopm=1 if ey< 12345.28 & year==2016
replace quasiopm=1 if ey< 12462.86 & year==2017
```

```
replace quasiopm=1 if ey< 12829.41 & year==2018
replace quasiopm=1 if ey< 13086 & year==2019

gen anchored=0 if ey!=.
replace anchored=1 if ey< 5044.989 & year==1979
replace anchored=1 if ey< 5761.052 & year==1980
replace anchored=1 if ey< 6310.693 & year==1981
replace anchored=1 if ey< 6764.871 & year==1982
replace anchored=1 if ey< 6949.128 & year==1983
replace anchored=1 if ey< 7230.47 & year==1984
replace anchored=1 if ey< 7503.891 & year==1985
replace anchored=1 if ey< 7632.162 & year==1986
replace anchored=1 if ey< 7902.327 & year==1987
replace anchored=1 if ey< 8230.074 & year==1988
replace anchored=1 if ey< 8669.544 & year==1989
replace anchored=1 if ey< 9065.614 & year==1990
replace anchored=1 if ey< 9499.606 & year==1991
replace anchored=1 if ey< 9759.158 & year==1992
replace anchored=1 if ey< 10089.98 & year==1993
replace anchored=1 if ey< 10323.27 & year==1994
replace anchored=1 if ey< 10630.51 & year==1995
replace anchored=1 if ey< 10956.6 & year==1996
replace anchored=1 if ey< 11162.04 & year==1997
replace anchored=1 if ey< 11375.32 & year==1998
replace anchored=1 if ey< 11596.92 & year==1999
replace anchored=1 if ey< 11986.08 & year==2000
replace anchored=1 if ey< 12402.26 & year==2001
replace anchored=1 if ey< 12576.94 & year==2002
replace anchored=1 if ey< 12848.39 & year==2003
replace anchored=1 if ey< 13229.08 & year==2004
replace anchored=1 if ey< 13529.74 & year==2005
replace anchored=1 if ey< 14174.02 & year==2006
replace anchored=1 if ey< 14519.72 & year==2007
replace anchored=1 if ey< 15264.32 & year==2008
replace anchored=1 if ey< 15007.78 & year==2009
replace anchored=1 if ey< 15134.97 & year==2010
replace anchored=1 if ey< 15804.65 & year==2011
replace anchored=1 if ey< 15945.77 & year==2012
replace anchored=1 if ey< 16235.69 & year==2013
replace anchored=1 if ey< 16690.9 & year==2014
replace anchored=1 if ey< 16690.9 & year==2015
replace anchored=1 if ey< 16848.36 & year==2016
replace anchored=1 if ey< 17008.82 & year==2017
replace anchored=1 if ey< 17509.08 & year==2018
replace anchored=1 if ey< 17859.26 & year==2019

// listwise deletion
drop if age>=18 | poor5>=. | famHH>=. | educhh>=. | agelead>=. | unemphh>=.
// dname
encode dname, gen(dname2)
// unique HH id
gen hid2 = 1000*hid + did
// looping over variables
foreach x in poor5 quasiopm anchored {
	proportion `x' [pw = hwgt], over(dname2) vce(cluster hid2)
}

corr poor5 quasiopm anchored

gen race=.
replace race=1 if ethnic_c==1
replace race=2 if ethnic_c==3
```

```
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10| ethnic_c==12)
replace race=4 if (ethnic_c==5| ethnic_c==7| ethnic_c==9| ethnic_c==11)

gen black=0 if race!=.
replace black=1 if race==2

gen latino=0 if race!=.
replace latino=1 if race==3

gen other=0 if race!=.
replace other=1 if race==4

**Quasi-OPM model predicted values for the US ALL controls
logit quasiopm unemphh lowed leadu25 singmom lead2534 leado54 nhhmem17 nhhmem65 highed multearn singdad black latino
other if age<18 & did==510 [pw=hwgt], cluster(hid)
*Penalties
margins, dydx(singmom)
*Predicted Values*
margins
*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))
*1970 Single Motherhood*
margins, at(singmom=(.106))
*Zero Single Motherhood*
margins, at(singmom=(0))

**Anchored model predicted values for the US ALL controls
logit anchored unemphh lowed leadu25 singmom lead2534 leado54 nhhmem17 nhhmem65 highed multearn singdad black latino
other if age<18 & did==510 [pw=hwgt], cluster(hid)
*Penalties
margins, dydx(singmom)
*Predicted Values*
margins
*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))
*1970 Single Motherhood*
margins, at(singmom=(.106))
*Zero Single Motherhood*
margins, at(singmom=(0))
```

****Code for Appendix II***

```
use $mydata/[user]/kidprevpen2024, clear

*Defining single mothers strictly as LONE mothers SINGMOM2*
gen singmom2=singmom if did==510
*NOT "head living with partner*
replace singmom2=0 if hpartner==1 & did==510
*NOT "couple with children and relatives"
replace singmom2=0 if hhtype==320 & did==510
*NOT "one parent with children and relatives"
replace singmom2=0 if hhtype==330 & did==510
*NOT "relatives living together (no family nucleus)"
replace singmom2=0 if hhtype==400 & did==510
*NOT "couple with children and nonrelatives"
replace singmom2=0 if hhtype==520 & did==510
*NOT "one parent with children and nonrelatives"
replace singmom2=0 if hhtype==530 & did==510
*NOT "couple with children and relatives and nonrelatives"
replace singmom2=0 if hhtype==620 & did==510
*NOT "one parent with children and relatives and nonrelatives"
replace singmom2=0 if hhtype==630 & did==510
*NOT "relatives and nonrelatives living together (no family nucleus)"
```

```
replace singmom2=0 if hhtype==700 & did==510
*NOT “nonrelatives living together”
replace singmom2=0 if hhtype==800 & did==510
*NOT HHs with more than one adult
replace singmom2=0 if nhhmem-nhhmem17>1 & did==510
tab singmom singmom2 if age<18 & did==510

// combined family variable2
gen famHH2 = 1
replace famHH2 = 2 if singmom2==1
replace famHH2 = 3 if singdad==1
label define famlab2 1 "Couple" 2 "Single Mom" 3 "Single Dad", replace
label val famHH2 famlab2

*Defining single mothers as Non-Couple HHs SINGMOM3*
gen singmom3=singmom if did==510
*NOT “head living with partner*
replace singmom2=0 if hpartner==1 & did==510
*NOT “couple with children and relatives”
replace singmom3=0 if hhtype==320 & did==510
*NOT “couple with children and nonrelatives”
replace singmom3=0 if hhtype==520 & did==510
*NOT “couple with children and relatives and nonrelatives”
replace singmom3=0 if hhtype==620 & did==510
tab singmom singmom3 if age<18 & did==510

// combined family variable3
gen famHH3 = 1
replace famHH3 = 2 if singmom3==1
replace famHH3 = 3 if singdad==1
label define famlab3 1 "Couple" 2 "Single Mom" 3 "Single Dad", replace
label val famHH3 famlab3

*alternative prevalences
tabstat singmom singmom2 singmom3 if did==510 & poor5!=. & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. &
nhhmem17!=. & nhhmem65!=. & highed!=. & multearn!=. & age<18 [w=hwgt], stats (mean semean n)

*alternative penalties
logit poor5 b1.famHH2 b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH2)

logit poor5 b1.famHH3 b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH3)
```

<u>Code for Appendix IV*</u>**

```
use $mydata/[user]/kidprevpen2024, clear

gen immlead_a=immigr*lead if did==510
egen immlead=max(immlead_a) if did==510, by(hid)

gen noncit=0 if citizen==1000 & did==510
replace noncit=0 if citizen==1300 & did==510
replace noncit=1 if citizen==2000 & did==510
gen noncitlead_a=noncit*lead if did==510
egen noncitlead=max(noncitlead_a) if did==510, by(hid)

*Penalties with immigrant adjustments*
logit poor5 i.immlead i.noncitlead b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if age<18 & did==510
[pw=hwgt], cluster(hid)
margins, dydx(famHH)
```

```
logit poor5 i.immlead i.noncitlead unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed
multearn if age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.144411))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*Penalties for Latino Sub-sample (table 3)*
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if latino==1 & age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH emphh educhh agecat)

*Penalties for Latino people with immigrant adjustments*
logit poor5 i.immlead i.noncitlead b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if latino==1 & age<18
& did==510 [pw=hwgt], cluster(hid)
margins, dydx(famHH)

logit poor5 i.immlead i.noncitlead unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed
multearn if latino==1 & age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.144411))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))
```

**Code for Appendix V*

```
use $mydata/[user]/kidprevpen2024, clear

*keep only children in US 2018 dataset
keep if did==510 & age<18

// variable for original sort order
gen id = _n

// copying original values
foreach x in famHH emphh leadeduc agecat {
	clonevar `x'_orig = `x'
}

// getting observed tabulations
foreach x in famHH emphh leadeduc agecat {
	tab `x'
	tab `x' [aw = hwgt]
}

*Actual single mother prevalence 8,924.3253, 0.1894
```

```
// dummy variables for sorting observations
gen mided = leadeduc==2
gen midage = agecat==3
gen oneearn = emphh==1

** REGRESSION **
// model predicting poverty
logit poor5 i.famHH b3.agecat b1.emphh b2.leadeduc nhhmem17 nhhmem65 i.race [pw = hwgt], cluster(hid)
// overall predicted probability of poverty with observed values for predictors
margins

** COUNTERFACTUAL WITH CROSS-NATIONAL MEDIAN SINGLE MOTHERHOOD **
*singmom prevalence would be .1465 (n=6903; reassign 2021)

// setting initial seed for random number generation

// to obtain results with different random reassignments, change the 'set seed' value or remove the command
set seed 123456

// conducting simulation 5 times
forvalues i = 1/5 {
di "SIMULATION `i'"
quietly gen r = runiform()

// reassigning single motherhood: moving 2735 from single mother to married
quietly gsort -singmom r
quietly recode famHH (2 = 1) in 1/2735
tab famHH [aw = hwgt]

// predicted poverty
margins

// restoring initial conditioons
quietly replace famHH = famHH_orig
drop r
sort id
}

** COUNTERFACTUAL WITH 1970 SINGLE MOTHERHOOD **
*singmom prevalence would be 0.106 (n=4995, reassign 3930)

// setting initial seed for random number generation

// to obtain results with different random reassignments, change the 'set seed' value or remove the command
set seed 123456

// conducting simulation 5 times
forvalues i = 1/5 {
di "SIMULATION `i'"
quietly gen r = runiform()

// reassigning single motherhood: moving 4370 from single mother to married
quietly gsort -singmom r
quietly recode famHH (2 = 1) in 1/4370
tab famHH [aw = hwgt]

// predicted poverty
margins

// restoring initial conditioons
quietly replace famHH = famHH_orig
drop r
```

```
sort id
}

** COUNTERFACTUAL WITH ZERO SINGLE MOTHERHOOD **
// reassigning all from single mother to married
quietly recode famHH (2 = 1)
tab famHH [aw = hwgt]

// predicted poverty
margins

// restoring initial conditioons
quietly replace famHH = famHH_orig
```

<u>Code for Appendix VIII</u>**

```
use $mydata/[user]/kidprevpen2024, clear

gen native=0 if ethnic_c!=.
replace native=1 if ethnic_c==5 & did==510

gen asian=0 if ethnic_c!=.
replace asian=1 if ethnic_c==7 & did==510
replace asian=1 if ethnic_c==9 & did==510

*poverty rates and prevalences
tabstat poor5 unemphh lowed leadu25 singmom if poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=.
& nhhmem65!=. & highed!=. & multearn!=. & native==1 & age<18 & did==510 [w=hwgt], by(did) stats (mean semean n)

tabstat poor5 unemphh lowed leadu25 singmom if poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=. & nhhmem17!=.
& nhhmem65!=. & highed!=. & multearn!=. & asian==1 & age<18 & did==510 [w=hwgt], by(did) stats (mean semean n)

*penalties & simulations for natives
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if native==1 & age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH emphh educhh agecat)

logit poor5 unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed multearn if native==1 &
age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*penalties & simulations for asians
logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 if asian==1 & age<18 & did==510 [pw=hwgt],
cluster(hid)
margins, dydx(famHH emphh educhh agecat)

logit poor5 unemphh lowed leadu25 singmom singdad lead2534 leado54 nhhmem17 nhhmem65 highed multearn if asian==1 &
age<18 & did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins
```

```
*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))
```

<u>Code for Appendix IX*</u>**

```
use $mydata/[user]/kidprevpen2024, clear

** REGRESSION WITH ONLY SINGLE MOTHERHOOD AND NO OTHER INDEPENDENT VARIABLES **
logit poor5 i.singmom if age<18 & did==510 [pw=hwgt], cluster(hid)
margins, dydx(singmom)

logit poor5 singmom if age<18 & did==510  [pw = hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

** REGRESSION OMITTING EDUCATION, EMPLOYMENT AND AGE But Including Other Controls **
logit poor5 i.singmom nhhmem17 nhhmem65 i.race if age<18 & did==510 [pw=hwgt], cluster(hid)
margins, dydx(singmom)

logit poor5 singmom singdad nhhmem17 nhhmem65 i.race if age<18 & did==510  [pw = hwgt], cluster(hid)

*Predicted Values of Poor5*
margins

*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*MODEL WITH ALTERNATIVE DEFINITION OF HH EMPLOYMENT AS HH FTEs
*Code number of full-time employees in 2018 US dataset
gen nadult=nhhmem-( nhhmem17+ nhhmem65) if did==510
gen fte=(hourstot*weeks)/(2080*nadult) if did==510
egen hhfte=sum(fte) if did==510, by(hid)

logit poor5 b1.famHH hhfte b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if age<18 & did==510 [pw=hwgt], cluster(hid)
margins, dydx(famHH hhfte)

logit poor5 hhfte lowed leadu25 singmom lead2534 leado54 nhhmem17 nhhmem65 highed singdad black latino other if age<18
& did==510 [pw=hwgt], cluster(hid)

*Predicted Values of Poor5*
margins
```

```
*Cross-National Median Single Motherhood Prevalence*
margins, at(singmom=(.14654))

*1970 Single Motherhood*
margins, at(singmom=(.106))

*Zero Single Motherhood*
margins, at(singmom=(0))

*NOTES IN TEXT ABOUT EMPLOYMENT RATES OF SINGLE MOTHER HHS
// check employment rates among single mothers in US
tabstat unemphh if singmom==1 & age<18 & lowed!=. & leadu25!=. & poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. &
mhnk!=. & nhhmem17!=. & nhhmem65!=. & highed!=. & multearn!=. & black!=1 & latino!=1 & other!=1 & did==510
[w=hwgt], by(did) stats (mean sd semean n)

tabstat multearn if singmom==1 & age<18 & lowed!=. & leadu25!=. & poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. &
mhnk!=. & nhhmem17!=. & nhhmem65!=. & highed!=. & unemphh!=. & black!=1 & latino!=1 & other!=1 & did==510
[w=hwgt], by(did) stats (mean sd semean n)

tabstat nearn if singmom==1 & age<18 & lowed!=. & leadu25!=. & poor5!=.  & lead2534!=. & leado54!=. & fhnk!=. & mhnk!=.
& nhhmem17!=. & nhhmem65!=. & highed!=. & black!=1 & latino!=1 & other!=1 & did==510 [w=hwgt], by(did) stats (mean
semean p10 p25 p50 p75 p90 sd n)
```

<u>Code for Appendix XI*</u>**

```
use $mydata/[user]/kidprevpen2024, clear

*define and equivalize income components & poverty
*market income
gen factoreq=hifactor/(sqrt(nhhmem))
gen marketpov=.
replace marketpov=0 if factoreq>= povl5 & factoreq!=.
replace marketpov=1 if factoreq< povl5 & factoreq!=.

*post-fisc minus public transfers
gen pubtransfer= hitransfer-(hiprivate+hi33)
gen nopubeq= (dhi-pubtransfer)/(sqrt(nhhmem))
gen nopubpov=.
replace nopubpov=0 if nopubeq>= povl5 & nopubeq!=.
replace nopubpov=1 if nopubeq< povl5 & nopubeq!=.

*post-fisc income minus family benefits (hi41)
gen nofameq =(dhi-hi41)/(sqrt(nhhmem))
gen nofampov=.
replace nofampov =0 if nofameq >= povl5 & nofameq!=.
replace nofampov =1 if nofameq < povl5 & nofameq!=.

*post-fisc income minus unemployment benefits (hi42)
gen nounempeq =(dhi-hi42)/(sqrt(nhhmem))
gen nounemppov=.
replace nounemppov =0 if nounempeq >= povl5 & nounempeq!=.
replace nounemppov =1 if nounempeq < povl5 & nounempeq!=.

*post-fisc minus alimony and child support
gen nopriveq =(dhi-hi521)/(sqrt(nhhmem))
gen noprivpov=.
replace noprivpov =0 if nopriveq >= povl5 & nopriveq!=.
replace noprivpov =1 if nopriveq < povl5 & nopriveq!=.

*all children
tabstat marketpov nopubpov nofampov nounemppov noprivpov if age<18 [w=hwgt], stats(mean) by(dname)
*children in single mom HHs
```

```
tabstat marketpov nopubpov nofampov nounemppov noprivpov if age<18 & singmom==1 [w=hwgt], stats(mean) by(dname)

*Black, Latino & white children in US in 2018
gen race=.
replace race=1 if ethnic_c==1
replace race=2 if ethnic_c==3
replace race=3 if (ethnic_c==2 | ethnic_c==4| ethnic_c==6 | ethnic_c==8 | ethnic_c==10| ethnic_c==12)
replace race=4 if (ethnic_c==5| ethnic_c==7| ethnic_c==9| ethnic_c==11)

gen black=0 if race!=.
replace black=1 if race==2

gen latino=0 if race!=.
replace latino=1 if race==3

gen other=0 if race!=.
replace other=1 if race==4

tabstat marketpov nopubpov nofampov nounemppov noprivpov if age<18 & did==510 [w=hwgt], stats(mean) by(race)

*Estimate model on US 2021

logit poor5 b1.famHH b1.emphh b2.educhh b3.agecat nhhmem17 nhhmem65 i.race if age<18 & did==964 [pw=hwgt],
cluster(hid)
margins, dydx(famHH educhh emphh agecat)
```