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EdWorkingPaper No. 25-1302

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VERSION: October 2025

Suggested citation: Sorensen, Lucy C., Melissa Arnold Lyon, Ji Hyun Byeon, and Stephen B. Holt. (2025). Contemporary Child Labor and Declining School Attendance in the U.S.. (EdWorkingPaper: 25-1302). Retrieved from Annenberg Institute at Brown University: https://doi.org/10.26300/hbcw-xc84

Contemporary Child Labor and Declining School Attendance in the U.S.

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Abstract. The United States has experienced a 400% increase in reported child labor violations over the past decade, coinciding with declines in K-12 school attendance and enrollment. We examine the causal relationships between these patterns with microdata from the American Community Survey (ACS) from 2005 to 2023. Using a shift-share instrumental variable approach, our findings show that increased local demand for illegal child labor leads to higher youth employment in high-violation industries, longer work hours, and lower school attendance, particularly among Black youth and youth living on farms. A 10-percentage-point increase in the local share of employment in high child labor violation industries leads to a 7-percentage-point decline in public school attendance for children and youth aged 6 to 17. Results underscore the need to reevaluate labor protections and strengthen enforcement to prevent economic pressures from pulling vulnerable, young students away from school.

Data availability. All data and code used in this article will be posted on OpenICPSR or a similar public repository upon publication.

Disclosure. The authors have no funding sources or conflicts of interest to disclose. This project does not involve human subjects research and as such is exempt from IRB approval.

[1] Lucy Sorensen was at University at Albany during the research but has since moved to Learning Policy Institute.

Introduction

Public school attendance among school-age children in the United States has declined sharply in recent years. Between the 2015-16 and 2021-22 school years, overall school enrollment dropped from over 84% to just below 79% (Goulas, 2024). Chronic absenteeism nearly doubled over the same period, with an additional 6.5 million students now missing more than 10% of the school year (Dee, 2024). Student attendance has always been a concern in U.S. schools, but the scale and persistence of the recent declines are striking and raise questions about their long-term implications for public education (Joseph, 2025).

Several factors may contribute to these trends. School attendance was declining before the COVID-19 pandemic disruptions to learning, but the pandemic further increased transitions into home and private schooling, while also pushing some students out of the education system altogether (Cohen, 2023; Diliberti et al., 2024). Districts have responded with interventions such as early warning systems and home visits, yet many leaders remain skeptical about their effectiveness (Diliberti et al., 2024). More broadly, scholars have emphasized that student attendance reflects a complex set of ecological factors—such as health, housing, transportation, and economic stability—many of which lie beyond schools' direct control (Childs & Lofton, 2021; Singer et al., 2021).

One phenomenon long tied to school attendance but rarely considered in contemporary debates over student disengagement is child labor. Over the same period that student absences surged, documented child labor violations also escalated. Since 2015, reported child labor violations have increased by more than 400%, with a particularly steep surge following the pandemic (U.S. Department of Labor, 2025). In 2023 alone, the U.S. Department of Labor reported a 50% year-over-year increase in the number of minors employed in violation of child

labor laws. Investigative reporting has documented widespread exploitative conditions, especially among migrant children, that directly interfere with their ability to attend school (for example, Dreier, 2023). The historical link between compulsory school attendance and child labor laws underscores that these issues have long been deeply interconnected (Fliter, 2018): when labor demand draws young people into work, educational participation is undermined. This connection also raises broader equity questions, as disadvantaged youth are more likely to face pressure to enter the workforce at the expense of sustained schooling.

This study examines the effects of local demand for child labor on school attendance in the United States. We ask three main questions: (1) How have school attendance patterns and youth labor rates evolved over the past two decades? (2) What is the causal impact of local reliance on child-labor-intensive industries on school attendance? and (3) How are these effects distributed across subgroups defined by age, gender, race/ethnicity, socioeconomic status, immigrant status, and agricultural location?

There is no universal definition of child labor (Edmonds, 2009). The term *child* can refer to children, adolescents, or minors who are required to attend school. The term *labor* is also ambiguous, as it can include not only formal labor market participation but also informal work such as chores and household tasks. Policy interests have narrowed the definition to harmful aspects of child labor, as exemplified by the International Labour Organization's (2024) definition of child labor as work that is "mentally, physically, socially or morally dangerous and harmful to children and/or interferes with their schooling." Empirically, what constitutes harmful labor for children remains an unsettled question. Practically, however, direct violations of child labor protection laws can be understood as harmful. As such, in this study, we operationalize

child labor as employment of minors in violation of the child labor regulations in the Fair Labor Standards Act (FLSA).

Our study builds on and connects three strands of prior research. Research from development economics has shown that child labor often reduces educational attainment in low- and middle-income countries (Bharadwaj et al. 2020; Bau et al., 2020; Beegle et al., 2009; Churchill et al., 2021; Dell, 2010; Edmonds, 2006; Emerson & Souza, 2011; Hossain, 2025; Piza et al., 2024). U.S. studies of youth employment, by contrast, have produced mixed evidence on whether working during the school year enhances skills or undermines educational and broader life outcomes (Baum & Ruhm, 2016; Chaplin et al., 2003; Hotz et al., 2002; Neumark & Wascher, 1995; Oettinger, 1999; Ruhm, 1997; Sabia, 2009; Staff et al., 2010; Tyler, 2003).[2] Third, research on labor markets shows that youth respond to specific community labor market conditions in choosing whether to remain in school or enter the workforce (Atkin, 2016; Black et al., 2005; Foote & Grosz, 2020; Morissette et al., 2015; von Simson, 2015). Yet almost no work has examined how *illegal and exploitative labor demand* affects educational outcomes in a high-income country context – the central question of this study.

To address our research questions, we use microdata from the American Community Survey (ACS) spanning 2005 to 2023 to measure employment and school attendance outcomes among children and youth ages 6 to 17. Our primary measure of local child labor demand is the share of local employment in industries with high rates of child labor law violations, constructed using the Quarterly Census of Employment and Wages and enforcement records from the Wage and Hour Division in the U.S. Department of Labor. To address the potential endogeneity of local labor market industry composition, we employ a shift-share instrumental variable approach

[2] There is also research on the effects of summer job programs for youth, which is more consistently positive for educational and labor market outcomes (Leos-Urbel, 2014; Li & Jackson-Spieker, 2022 Schwartz et al., 2021).

with locality and year fixed effects, leveraging variation from national industry shocks interacted with localities' historical industry composition (Bartik, 1991).

Our findings show that increases in local reliance on child-labor-intensive industries substantially reduce school attendance, with especially large effects among disadvantaged groups. A 10-percentage-point increase in the local share of employment in high-violation industries leads to a 6.9 percentage point decrease in public school attendance overall, by 20.2 percentage points among Black youth, and by 29.1 percentage points among youth living on farms. The effects are concentrated among older teens, who also increase their weekly work hours and employment in high-violation industries. We also observe shifts from public schooling into private or homeschooling, suggesting some parents may seek more flexible arrangements to accommodate youth work. (Private schooling and homeschooling cannot be differentiated in our data). We conduct a variety of falsification tests to ensure that the shift-share instrumental variable is not associated with local demographic changes.

This study makes several contributions. First, it provides the first causal evidence linking child labor to schooling outcomes in a high-income country. The high-income country context allows for investigation of how child labor affects schooling choices in settings where worker protections are more robust and cultural norms discourage intensive child work. Second, it distinguishes exploitative and illegal child labor from general adolescent employment, offering a new lens on the tradeoffs between work and human capital formation. Distinguishing exploitative employment from general employment helps to establish when working inhibits or encourages human capital development through schooling. Third, it introduces a novel shift-share measure of local child labor demand, providing a new tool for studying how labor market shocks affect specific vulnerable worker populations. Finally, it connects two pressing post-

pandemic trends—rising child labor and declining school attendance—highlighting their intersection. Together, the results suggest that enforcing child labor laws is not only critical for protecting youth but also for sustaining fundamental goals of universal public education.

Background

History and Policy Context

From the late 19th century to before World War II, children in the U.S. worked in home industries, street trades, mines, and factories, often facing hazardous conditions that put their health and education at risk (Whittaker, 2004). In response, state and federal policymakers introduced regulations to restrict children from the workforce. However, even after new legislation, labor shortages during World War II led to a surge in child employment, particularly in agriculture, manufacturing, and service industries (Magee, 1944). The number of children working in violation of federal labor standards rose sharply, while school enrollment declined. Many youths left school to support their families, a disruption that had long-term consequences for their earnings and economic mobility (Ichino & Winter-Ebmer, 2004). By the late 20th century, however, high school graduation became a norm with rising high school graduation and college enrollment and a decline in child labor (Goldin, 1994). That said, youth labor persists today, driven by low wages, flexible schedules, and employer preferences for young workers (Bachman, 2000; Kruse & Mahony, 2000).

The FLSA of 1938 is the primary lever for federal child labor governance. The FLSA sets baseline restrictions on minor employment with a particular emphasis on age restrictions. FLSA provisions mostly relate to children under 16: children aged 14 and above can work legally across industries, while those aged 12 and above can work in agricultural settings. Children of any age can work as child performers, for family businesses (outside of manufacturing and mining), and for businesses with annual sales under $500,000 or not engaged in interstate

commerce, as these are all exempt from the FLSA. Minors under 16 are limited in the number of hours they can work, but the FLSA does not place limits on hours worked for minors aged 16 and 17. The FLSA does prohibit minors under 18 from working in hazardous, non-agricultural industries and minors under 16 from working in hazardous agricultural occupations. Violations of FLSA child labor policies are investigated and enforced by the Wage and Hour Division of the Department of Labor.

The child labor provisions of the FLSA interact with both state policies and international commitments. At the state level, federal U.S. child labor policies in the FLSA should preempt state laws. This means that aspects left out of the FLSA are regulated at the state level, and aspects that are in the FLSA can legally be further regulated in the states, accepting FLSA provisions as a "floor." States also play a role in child labor policy enforcement because federal capacity to enforce child labor laws is constrained; under FLSA Section 211(b), the federal agency may utilize the services of state and local labor agencies while reimbursing them for their services. At the international level, the U.S. ratified the ILO C182-Worst Forms of Child Labor Convention in 1999, which commits the U.S. to prohibiting employment of minors under 18 in hazardous industries; however, as described above, the U.S. federal government still allows minors aged 16-17 to work in hazardous occupations in agriculture. The U.S. is one of just two nations (alongside Somalia) that has not ratified the Convention on the Rights of the Child. The U.S. is also one of just 11 countries that has not ratified the International Labour Organization (ILO) C138-Minimum Age Convention, which would prohibit employment of minors under 15.

Conceptual Framework

We conceptualize the decision for a child to seek employment as one that is often initiated by household economic necessity (Basu & Van, 1998; Basu et al., 2010; Edmonds,

2005; Edmonds & Schady, 2012). When families face financial constraints, they may view children's potential earnings as an essential supplement to household income, creating a push factor toward minor employment. In areas with low demand for child labor, minors may work a few hours a week or on the weekends without meaningfully affecting their schooling. Such work may even improve long-run outcomes as minors may gain valuable knowledge and skills that make them more employable or keep them from criminal activity. Indeed, prior work on the effects of adolescent labor suggests that while employed youth engage in deviant behavior at higher rates (Rauscher, 2011), this operates largely through selection effects. After accounting for selection, employed youth engage in fewer delinquent behaviors (Brame et al., 2004; Paternoster et al., 2003; Apel et al., 2008) and have higher employability later in life (Carr et al., 1996; Hotz et al., 2002; Mihalic & Elliott, 1997; Ruhm, 1997), consistent with potential benefits of modest youth employment.

In areas with high demand for child labor, market forces could significantly alter this trajectory. Growth in demand for child labor may cause minors to work significant hours to capitalize on labor market opportunities, taking time away from studying (Kalenkoski & Pabilonia, 2009; 2012) and/or shifting long-term academic expectations (Marsh & Kleitman, 2005; Steinberg et al., 1993). Prior research on intensive youth employment has consistently found higher school absenteeism (for a review, see Neyt et al., 2019), reduced academic performance (Sabia, 2009; Staff et al., 2010; Tyler, 2003), and increased likelihood of school dropout (Apel et al., 2008), among youth who work. If family economic circumstances drive the supply of adolescent labor, low-income households would face this tradeoff between school attendance and intensive labor more frequently. Consistent with this possibility, prior work has persistently documented higher absenteeism among economically disadvantaged students

(Bartanen, 2020; Gershenson et al., 2017; Gottfried, 2009; Liu et al., 2021; Morrissey et al., 2014; Ready, 2010; Romero & Lee, 2008, 2008). Local labor markets with high demand for child labor could provide additional incentive for youth—and particularly youth in low-income households—to trade some marginal school time for additional work hours.

In view of the established patterns of more intensive adolescent employment leading to worsening attendance and deteriorating performance in school, we posit that high demand for child labor could trigger a cycle of disengagement from school. As Kirksey and colleagues (2024) note, such a cyclical pattern can arise because absences weaken student performance, and anxiety from the resulting poor performance in class can drive continued absenteeism and withdrawal from school. In addition, more robust local job opportunities that do not require a college degree could disincentivize students from pursuing higher levels of education (Betts & McFarland, 1995; Foote & Grosz, 2020), further devaluing investments in secondary education. As educational gaps widen and labor market attachments strengthen, we hypothesize that the school-to-work balance increasingly tilts toward labor, potentially culminating in permanent school dropout and full labor market integration. This outcome is concerning because employment that is available to minors is often low-skill and low-wage, leading to potential long-term implications for human capital development and intergenerational economic mobility. Appendix Figure A1 summarizes these hypothesized causal pathways.

Data

This study uses pooled annual microdata on children and youth aged 6 through 17 from the American Community Survey (ACS) between 2005 and 2023, linked to local economic indicators from the Quarterly Census of Employment and Wages and incident-level data on child

labor federal violations from the Department of Labor Wage and Hour Division. Because the ACS data does not contain a county identifier for counties with less than 65,000 population, we aggregate all dependent and independent variables at the Public Use Microdata Area (PUMA) level. PUMAs are non-overlapping geographic areas containing no fewer than 100,000 population each.[3] Our final analytical sample includes 2,461 PUMAs tracked over 19 years. Descriptive statistics of all key measures are provided in Table 1.

American Community Survey

From the ACS individual-level data, we extract several key variables. First, we observe whether each individual aged 6 to 17 attended school at any time during the last three months, by school type (public or private/home school).[4] Second, we extract information on employment for youth aged 16-17 (the only ages for which employment information is available). We measure working status as whether the individual worked for pay at a job or business in the last week. To examine the intensive margin of impacts on youth labor, we also create a continuous variable for all working youth based on how many hours the person usually worked each week during the past 12 months. We further use the NAICS industry code variable to identify whether the individual worked in a high-violation industry for their employment, with high-violation defined as described in the next subsection. For all outcomes, we calculate averages at the PUMA-year

[3] We use geographic correspondence matrices from the University of Missouri Census Data Center to allocate variables from the county level to the PUMA level by population. Because PUMA designations are not constant across Census periods, we use another correspondence matrix to translate all variables to the PUMA-22 level, which is based on 2020 Census PUMAs.

[4] The attendance question asks, "At any time IN THE LAST 3 MONTHS, has this person attended school or college? Include only nursery or preschool, kindergarten, elementary school, home school, and schooling which leads to a high school diploma or a college degree." The survey then has the option of checking one of three boxes: (1) No, has not attended in the last 3 months; (2) Yes, public school, public college; or (3) Yes, private school, private college, home school. We consider checking either the second or third box as an indicator of school attendance but focus primarily on public school attendance.

level for the full school-aged population (ages 6-17), by age group, by gender, by race/ethnicity, by immigrant status, by poverty status, and by family farm status.

Child Labor Violations

To identify industries with high levels of child labor violations, we use data from the U.S. Department of Labor Wage and Hour Compliance Action Data. This dataset includes all compliance actions since the 2005 fiscal year. Among these compliance actions, we restrict the data to only contain actions for which there is at least one violation under the FLSA Child Labor statute. For each of these actions, we observe relevant dates, the employer name and location, the NAICS industry code, the number of child labor violations under FLSA, the number of minors found employed in violation, and the amount of civil money penalties assessed. Over the period in question (2005-2023), there was an initial reduction in the number of violations followed by a substantial rise (see Appendix Figure A2).[5] Appendix Figure A3 shows the geographic distribution of investigated child labor violations, with higher prevalence occurring in some Midwestern and Western regions.

We use this data to identify industries most prone to receive child labor violations relative to their size. For all 4-digit NAICS industry codes, we calculate separately the number of *violations* and number of *minors found in violation* under FLSA child labor regulations between 2005 and 2023 per 1,000 employees in that industry.[6] We define an industry as "high-violation" if it is contained in both the top quartile of violations per 10,000 employees and in the top quartile of minors in violation per 10,000 employees. From this list, we remove industries in the

[5] It may initially appear like violations have been dropping in the past couple of years, but this is an artifact of how and when violations are reported. Instead, the recent drop reflects that these investigations are still pending. Official sources have shown that in fact reported violations have increased significantly in recent years (U.S. DOL, 2025).
[6] For the denominator of number of employees in that industry nationally we use the average employment during the 2005-2023 time period.

bottom quartile of national employment, since they may appear erroneously as high violation because of the small employment denominator. These three rules yield a final list of 50 industries that incur a significant portion of all U.S. child labor violations, shown in Appendix Table A1. Some of the worst offenders on this list include amusement parks and arcades (with 4.4 violations per 10,000 employees), specialty food stores (with 2.2 violations per 10,000 employees), and vegetable and melon farming (with 2.2 violations per 10,000 employees).[7]

Quarterly Census of Employment and Wages

We employ Quarterly Census of Employment and Wages (QCEW) data from the U.S. Bureau of Labor Statistics to track employment statistics by 4-digit NAICS industry, locality, and year between 2004 through 2023. Importantly for our shift-share approach described in the following section, we need to track national employment growth in each industry between the baseline year and each subsequent year (the "shift"). We also need to calculate for each locality the proportion of local employment in each 4-digit NAICS industry during the baseline year of 2004 (the "share"). We use QCEW annual employment data for calculating both figures. The endogenous treatment variable of interest in our study is the proportion of employment in each PUMA and year that exists in industries identified as high-child-labor-violation. Because QCEW measures employment at the county level, we use allocation weights from the Missouri Census Data Center (MCDC) Geographic Correspondence Engine to recalculate treatment at the PUMA-year level. Figure 1 presents the average share of employment in high child labor violation industries in the U.S. by PUMA across 2005 to 2023. Reliance on high violation industries is

[7] These values of number of violations per 10,000 employees appear low for multiple reasons. First, they only include violations of federal law, not state law. Second, they are scaled by the entire labor force, not just the youth labor force. And third, enforcement of child labor is fragmented and underfunded. In general, there is little incentive for either employers or employees to report suspected child labor violations, since the employment is often taken due to financial necessity. This is why we only use violations data only to identify high child labor industries in aggregate and not as a key variable in our analysis.

spread fairly evenly across the country, although with certain small areas such as ones located in Florida, Arizona, Texas, California, Michigan, and Colorado, relying more heavily on industries prone to child labor violations.

Demographic and Socioeconomic Covariates

To account for changes in local populations and economies over time, we collect covariates from a variety of data sources. From the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute, we obtain annual local population estimates by age, sex, race (Black / White / other), and national origin (Hispanic / not). We obtain the local unemployment rate from the Local Area Unemployment Statistics from the U.S. Bureau of Labor Statistics. We also obtain the percent of children aged 5 to 17 in poverty and the median household income from the Small Area Income and Poverty Estimates from the U.S. Census Bureau. Again, we use the allocation matrix from the MCDC to recalculate all measures at the PUMA-year level. Finally, from the ACS microdata, we calculate the percent of children aged 6 to 17 in each PUMA and year that are born outside of the U.S. to non-American parents.

Methods

Our study employs a shift-share instrumental variable approach to assess the impact of local reliance on illegal minor employment on school attendance rates (Bartik, 1991).

Conceptually, this study examines how local demand for child labor influences youth schooling outcomes. Our preferred measure of local child labor demand is the share of employment in each PUMA and year that is classified as high violation. Unfortunately, we cannot expect this measure to be exogenously determined. The opening of a shopping mall in a community, for example, might both increase demand for youth labor and also have a variety of

other economic and demographic impacts on the community. The closing of a manufacturing plant might reduce demand for youth labor, but it could occur as the result of cumulatively growing economic pressures facing the community. For these reasons we use an instrumental variable as a source of exogenous variation in local child labor demand.

Specifically, we use an instrumental variable designed to mimic a shift-share instrument. Shift-share instrumental variables have a long history in economics and have received recent attention regarding their econometric assumptions and design (Borusyak et al., 2025; Goldsmith-Pinkham et al., 2020). The classic example comes from Bartik's (1991) study in which he aims to isolate exogenous variation in local employment rate changes arising from the interaction between county industrial structure and national industrial trends. The instrument uses as its foundation the fact that total county employment growth equals the sum across all industries of each industry's share of employment multiplied by employment growth in that industry. To isolate only industrial changes coming from external shocks, the shift-share instrument replaces local industry-specific employment growth figures with national industry-specific employment figures. These represent the "shifts." It also sets the county industrial structure as fixed at a baseline point in time to avoid endogenous, simultaneous economic changes happening in the county. This baseline industrial structure, measured as the share of employment in each industry, represents the "shares." Summing across industries, the shifts multiplied by the shares produce the classic shift-share instrument.

Our empirical approach uses this same general logic. To avoid problems of endogeneity associated with the child labor demand measure (i.e., the share of local employment in high-violation industries), we instrument child labor demand with the following Bartik-inspired instrument z_{jt}:

$$z_{jt} = \sum_k w_{jk} e_{kt}$$

This instrument is defined for each PUMA *j* in each year *t* as the sum across all high-violation industries *k* of the product of two terms: the share w_{jk} and the shift e_{kt}. The share measure equals, for each high-violation industry *k*, the proportion of total employment in PUMA *j* in 2004 that is assigned to that industry. We select 2004 because it is the year prior to the start of our panel dataset. The shift measure equals, for each high-violation industry *k*, the growth in that industry share nationally between year 2004 and year *t*, where 1 would represent no change over time in its national share of employment.[8]

Using this instrumental variable, we proceed with the following two stage estimation:

$$d_{ijt} = \beta_{10} + \beta_{11} z_{jt} + \beta_{12} X_{ijt} + \gamma_j + \delta_t + \delta_t \textstyle\sum_k w_{jk} + \varepsilon_{ijt} \qquad (1)$$

$$y_{ijt} = \beta_{20} + \beta_{21} \widehat{d_{ijt}} + \beta_{22} X_{ijt} + \gamma_j + \delta_t + \delta_t \textstyle\sum_k w_{jk} + \epsilon_{ijt} \qquad (2)$$

In the first stage, child labor demand measured as the PUMA-year share of employment in high-child-labor-violation industries, d_{ijt}, is regressed on the shift-share instrument z_{jt}. In the second stage, a measure of the proportion of children attending public school in PUMA *j* in year *t,* y_{ijt}, is regressed on the predicted local child labor demand from the first stage. We include PUMA fixed effects (γ_j) to account for any fixed characteristics of localities that could be related to both child labor demand and school attendance outcomes and include year fixed effects (δ_t) to account for any common trends over time. We also include a set of year fixed effects multiplied by the baseline share of PUMA employment in all high-violation industries ($\delta_t \sum_k w_{jk}$). Including this third set of fixed effects is best practice for shift-share instrumental variables

[8] A histogram of the Bartik shift-share instrument is shown in Appendix Figure A4 with a mean of 0.32, standard deviation of 0.08, and quite normal distribution.

estimation in panel data (Borusyak et al., 2025) and accounts for any differential trends over time for communities with higher or lower general reliance on high-child-labor-violation industries. Finally, we control for a set of time-varying covariates (X_{jt}) reflecting local demographic and socioeconomic conditions.[9] Standard errors are clustered at the PUMA level.

As with any other instrumental variable, the shift-share instrument must meet two main requirements to produce unbiased estimates through two-stage least squares. First, it must be relevant. Our first stage equation estimates presented in Appendix Table A2 show that a 1 unit increase in the shift-share instrument has an average effect of 0.24 on our measure of child labor demand. This implies that a 100-percentage point change in the shift-share measure translates into a 24-percentage point change in actual local reliance on high violation industries. The first stage Kleibergen-Paap Wald F-statistic, which adjusts for PUMA-level clustered standard errors, is 14.6. This value is above the traditional rule-of-thumb threshold for strong instruments of 10 (Staiger & Stock, 1997); however, it is lower than some modern recommended criteria for fully eliminating size distortion in instrumental variable estimation (Lee et al., 2022).

The second requirement of an instrumental variable is exogeneity: the instrumental variable should not be correlated with the error term. Borusyak, Hull, and Jaravel (2025) simplify this assumption for the case of the shift-share instrument to note that identification requires either the "shares" *or* the "shifts" to be exogenously determined. They consider primarily the case of cross-sectional data, and so our required assumption is slightly weaker—that the shifts are exogenous conditional on PUMA fixed effects, year fixed effects, year-by-baseline share of high-violation employment fixed effects, and included covariates. We believe

[9] Our PUMA-level covariates include log population, share of population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

this condition to be reasonable and conduct falsification tests to ensure that the shift-share instrumental variable is not associated with local demographic changes in Appendix Table A3.[10]

We replicate these analyses for youth employment outcomes as an exploration of the most likely mechanism for effects of child labor demand on school attendance. We also replicate these analyses restricting the sample to certain subgroups, including by gender, race/ethnicity, household poverty status, immigrant status, and household farm status.

Results

Descriptive Trends in Schooling and Labor of School-Age Children

Before proceeding to estimation, we describe recent patterns and trends in the schooling and labor of school-aged children and youth. Figure 2 presents the percent of children and youth *not* attending public school between 2005 and 2023 across three age groups: ages 6 to 13, 14 to 15, and 16 to 17. Non-attendance in this context means not attending public school any time during the past three months.[11]

Among individuals aged 6 to 13, public school non-attendance declined noticeably following the Great Recession, but then gradually increased between 2011 and 2019, ending that decade at around 13 percent of children not attending public school. Of these, around 10 percent are attending private school or being home schooled (Appendix Figure A5). Younger teenagers aged 14 to 15 exhibited similar trends. The COVID-19 pandemic led to a huge shock in these

[10] Of all the demographic covariates examined, there are no significant effects of local child labor demand on any measures at the 95% level. There is one marginally significant effect of local child labor demand on percent black (coef=0.52, $p<0.1$), though this is small in magnitude and not more than would be expected by chance.

[11] These age groupings were chosen deliberately. We excluded five-year-olds because non-attendance is high among this group, many of whom have yet to enter the school system and for whom school attendance is not compulsory. 14 and 16 are common age thresholds for a variety of state and federal child labor regulations, below which certain legal protections apply. Outside of agriculture and entertainment, minors cannot work legally until they are 14 and cannot work legally for more than three hours on school days until they are 16. All states require school attendance until age 16, and many states require attendance beyond that age.

trends, with non-attendance increasing by over 5 percentage points among children aged 6 to 13 in 2020. There were similar jumps for teenagers, although to a slightly lesser extent. Public school attendance among younger children and teenagers has recovered somewhat in the years since the pandemic—but absence from school remains well above pre-pandemic levels in 2023, at around 15 percent for all age groups. Some but not all of this drop in public school attendance can be explained by growth in home schooling and private school attendance, as seen in Appendix Figure A5. Youth aged 16 to 17 have generally held higher rates of non-attendance at school, although younger children surpassed them in the post-pandemic years. Appendix Figure A6 shows that these school attendance rates vary greatly across population subgroups, with the most extreme outlier being children living on farms, less than half of whom report attending public school.

The primary hypothesis of this paper is that demand for child labor can pull youth out of school, with potentially detrimental long-term impacts. The ACS data only contains information on employment for individuals aged 16 and older, but we can examine trends in labor market indicators for this group of older teenagers over time. We do so in Figure 3, first looking at the proportion of minors aged 16 to 17 currently working at all. In 2005, around 40 percent of all youth in this age group were working, although this number dropped drastically during the Great Recession to around 25 percent. Since that time, youth have worked more and more each year, with around a 10-percentage point growth in the employment rate observed for this age group between 2010 and 2023. Working in industries with high rates of child labor violations has followed the same general trend over time, and the share of working youth in high-violation industries has grown markedly since the early 2000s. Consistent with the literature (Apel et al., 2008; Monahan et al., 2011), we consider working more than 20 hours per week a form of

intensive labor for minors that is likely to interfere with their schooling. The proportion of youth working over 20 hours a week also declined markedly during the Great Recession (from 2008 to 2010) but has been trending gradually upwards since 2011, hovering currently at around 15 percent.

Clearly, both chronic absence from school and participation in time-intensive or hazardous work are currently on the rise in the United States for school-age children. Our subsequent analyses investigate the extent to which demand for illegal child labor is driving some portion of these reductions in public school attendance.

Effects of Child Labor Demand on School Attendance

Table 2 presents the instrumental variable estimates of effects of the proportion of local employment in high child labor violation industries on public and private/home school attendance outcomes. We conduct analyses with the full sample and also split the sample into three age groups: 16 to 17, 14 to 15, and 6 to 13. Results in column 1 indicate that among all school-aged children, a 10-percentage point increase in child labor demand reduces public school attendance by 6.9 percentage points. It also increases private school or home school attendance by 5.8 percentage points.[12] These opposing changes leave 1.1 percentage point of school-aged children dropping out of schooling altogether—a meaningful drop representing over 500,000 children leaving any type of schooling.[13] It is also plausible that some of the children reported as attending home school might be doing so because parents seek to remove external accountability systems and in doing so open up more time for their children to work. Homeschooling as an opportunity for youth work flexibility has even driven some policy changes, as Florida recently

[12] As noted above, the ACS reports private and home schooling together as a single measure, so we cannot observe them separately.
[13] The 500,000 figure is based on 2021 population estimates of children aged 6 to 17 from the Census.

exempted all homeschooled teenagers from the work hour restrictions that apply to students attending public school (Tucker, 2024).

When we examine heterogeneity by age, we find the largest impacts among youth aged 16 to 17. Among this group, a 10-percentage point increase in child labor demand reduces public school attendance by 7.9 percentage points. We still find sizable decreases in public school attendance for younger ages, though, with a 7.5 percentage point decrease for ages 14 to 15 and a 6.9 percentage point decrease for ages 6 to 13. Private and home school attendance increases are only statistically significant for the youngest age group, for whom schooling is always compulsory. The large reduction in public school attendance among teenagers old enough to not be subject to compulsory schooling laws, with no real corresponding increase in private or home school attendance, indicates a likely dropout phenomenon.

The reduction in public school attendance among younger children, with partial offset by private or homeschooling, suggests more subtle mechanisms. Younger students may exhibit chronic absence from school so as to work, but they may also enter informal schooling arrangements such as homeschooling with less oversight over labor participation. Home school students have less exposure to mandatory reporters (individuals bound by law to report signs of abuse), and in some states, they can have no contact with mandatory reporters at all (Bartholet, 2019; Luck et al., 2025).

We further investigate heterogeneity by different student populations. Figure 4 presents these results graphically and Appendix Table A4 numerically. We examine differences by gender, race/ethnicity, poverty status, immigration status, and farm residence. We find that Black children and children on farms experience the largest adverse effects of increasing demand for child labor, although many of the confidence intervals overlap. In response to a 10-percentage

point increase in the share of local employment in high-violation industries, Black student attendance drops by 20.2 percentage points and attendance of students living on farms drops by 29.1 percentage points. Although some share of this public school attendance change is likely offset by transfers to home schooling or private schooling, a large remaining share represents Black children and children living on farms no longer attending school at all. Children in poverty also experience especially large effects of increasing demand for child labor. A 10-percentage point increase in the share of employment in high violation industries causes public school attendance to decrease by 9.1 percentage points for children in poverty. These heterogeneous findings illustrate that the negative effects of increased demand for child labor are experienced more acutely by children living in families with significant economic need.

Effects of Child Labor Demand on Adolescent Employment

Our main hypothesized mechanism in the link between community reliance on child labor and reduced school attendance is an increased likelihood that children and youth participate in intensive or exploitative work that interferes with their schooling. To test this mechanism, we estimate the effects of local child labor demand on labor outcomes for youth aged 16 to 17. (We lack information on work status for children under the age of 16.) These results are presented in Table 3 as instrumental variable estimates. Each coefficient estimate represents the impact of a 10-percentage point increase in the proportion of PUMA employment in high-violation industries on average youth employment outcomes.

Column 1 presents the effects this child labor demand measure has on the share of youth with any employment in the prior year. At this extensive margin, we see a 7.7-percentage point increase in the likelihood of any employment (marginally significant, $p<0.1$). With an average rate of 32 percent of this age group population typically working, a 7.7 percentage point increase

represents substantial growth (24%) in the number of teenagers participating in the labor market. Column 2 indicates that essentially the entirety of this growth in youth employment happens in industries with high rates of child labor violations, even though they represent only 16 percent of all industries.

At the intensive margin, conditional on any work, we also see increases in the average number of hours worked per week among 16- and 17-year-olds (column 3). Each 10-percentage point increase in the share of high-child-labor-violation industries increases average weekly hours by 3.5 hours ($p<0.05$), or a 19 percent increase from the average 18.2 hours worked among youth reporting any employment. Finally, as might be expected given the increased employment in high-violation industries, we observe substantive increases in the likelihood of youth working over 20 hours weekly, of 12.9 percentage points among the working youth population (marginally significant, $p<0.1$). This is equivalent to a 28 percent increase from the average proportion of youth working over 20 hours.

The take-away findings from these results are quite clear: local demand for child labor increases work of youth aged 16 and 17 at both the extensive and intensive margins. These effects are most pronounced among high-violation industries and lead to large increases in youth working more than 20 hours per week. To the extent that there exists a tradeoff between work and school, these changes in working patterns help to explain how shifts in local labor demand translate into changes in youth attendance and engagement with school.

Robustness Tests

We show results from a number of alternative specifications, including instrumental variable estimation without any PUMA-level demographic or economic controls (Appendix Tables A5 and A6), reduced form estimation of the direct effects of the Bartik shift-share

instrument on attendance and work outcomes (Appendix Tables A7 and A8), and instrumental variable estimation without PUMA school-age population weights (Appendix Tables A9 and A10). All estimates from these alternative specifications are fully consistent with local child labor demand decreasing the share of children and youth attending public school and increasing the share of youth working. Reduced form estimates are slightly smaller in magnitude, though still statistically significant, which is to be expected given that these represent intent-to-treat effects of the Bartik shift-share instrument.

We also conduct a falsification check to provide an empirical test of the exclusion restriction. Specifically, we regress the set of PUMA-year-level demographic covariates on the share of local employment in high-violation industries using our preferred IV specification. As can be seen in Appendix Table A3, the local share of high-violation employment has null effects on all six demographic covariates. It is associated with a marginally significant ($p<0.1$), trivial increase in the percent of the population that is Black. The point estimate is below one percentage point. These additional tests suggest that our identification strategy captures pure effects of changes in local demand for child labor that do not reflect pre-existing demographic shifts, nor do they cause any new demographic shifts.

Discussion

The relationship between schooling and labor is longstanding and complex. While child labor in the U.S. is often perceived as an issue of the past (Goldin, 1994; Ichino & Winter-Ebmer, 2004; Whittaker, 2004), recent evidence suggests otherwise. Investigative journalism has uncovered a resurgence of exploitative labor practices affecting children and youth, particularly among migrant children (for example, Dreier, 2023). Reports indicate that these child laborers

struggle to attend school consistently and keep up with their education. The U.S. Department of Labor has also raised concerns about a significant rise in violations of child labor laws under the Fair Labor Standards Act (U.S. Department of Labor, 2025).

Simultaneously, education stakeholders have expressed growing alarm over increasing rates of chronic absenteeism and declining school enrollment (Attendance Works, 2023; Lieberman, 2024; Irwin et al., 2023). Notably, states that have recently weakened child labor regulations have also passed laws that make it easier for parents to withdraw their children from school for homeschooling (Sherer & Mast, 2023; Hroncich & Buckland, 2024), further complicating the intersection between labor and education among young people.

This study empirically examines the potential links between these two phenomena using a shift-share design to estimate the impact of local demand for illegal or exploitative child labor on school attendance and youth employment. Our findings suggest that a 10-percentage point increase in local child labor demand leads to a 7-percentage point decline in public school attendance for all youth and an 8-percentage point decline for youth aged 16 to 17. The effect is more pronounced among disadvantaged groups, with attendance declining at much higher rates for youth in poverty, Black youth, and youth living on farms. In terms of employment mechanisms, this same increase in child labor demand leads to an 8-percentage point increase in the likelihood of holding any job, an average increase of 3.5 hours in weekly hours, and a 13-percentage point increase in the likelihood of working more than 20 hours per week, among youth aged 16 to 17.

This research is among the first studies of contemporary child labor in the United States. As such, it offers a number of pathways for future research that can address present limitations and knowledge gaps. Notably, measuring child labor and illegal minor employment directly is

challenging due to underreporting and enforcement complexities, necessitating the use of proxy measures for local child labor demand. It is quite likely that a number of families are reporting that their children are attending school or being home schooled when they are not. Such measurement error could dampen our estimates. Additionally, we are unable to parse out differences between private school attendance and home schooling. Future research at the state or local level with more fine-grained data would expand our understanding of the relationship between home schooling and child labor.

The policy implications of these findings are significant. In the short-term, reducing absence from school improves student academic performance (Aucejo & Romano, 2016; Goodman, 2014). In the long-term, keeping students in school and ensuring they attain a high school diploma yields substantial benefits for individuals and society at large (Card, 1999; Lochner, 2011; Psyacharopoulos & Patrinos, 2018). Thus, the concurrent trends of rising child labor and declining school attendance warrant urgent policy attention. Three key policy avenues could help address these challenges: strengthening regulations, enhancing enforcement, and expanding educational support services.

First, state and federal policymakers could implement stronger and more consistent labor laws. Some of our federal labor laws are quite strong, such as the prohibition on working more than three hours on school nights for 14- and 15-year-olds. However, there are some conspicuous areas where policies could be strengthened, such as prohibiting minors under 18 from working in any hazardous occupations. At present, federal law prohibits minors from working in hazardous occupations outside of agriculture but permits work in hazardous occupations in agriculture

beginning at age 16.[14] States or the federal government could close other loopholes in child labor regulation, such as exemptions for child performers, family businesses, and small businesses. Governments could also make incremental improvement in a variety of policies such as enacting or tightening age certification requirements—there is presently no federal age certification requirement—so as to mitigate the adverse effects of youth labor on human capital development.

Second, federal and state authorities could enhance child labor law enforcement. Increasing resources for labor law enforcement at both state and federal levels would help ensure businesses comply with regulations regarding the employment of minors (Gerstein, 2024). At present, much of the enforcement of federal child labor policies happens at the state level, and the federal government then reimburses states for their efforts. This means that states have agency to increase the enforcement of federal laws without having to bear all the costs, even in the absence of new federal action. Another way to increase resources *and* enhance enforcement could be to levy higher fines for violators. The Wages and Hours Division recently changed its fine for confirmed child labor violations from $11,000 per minor in 2011 to $15,138 per violation in 2023 (U.S. Department of Labor, 2023). Although our timeframe falls short of observing the newly revised penalty, we speculate that the previous fine amount was not a strong disincentive for businesses.

Third, policymakers could expand educational support services in targeted ways. Federal or state governments could provide additional resources to public school systems to hire social workers and conduct outreach programs that could identify and assist students struggling with exploitative labor conditions. Authorities could target these resources in areas where there is a

[14] Permitting any hazardous work for minors under 18 is inconsistent with preexisting international commitments, so addressing this so-called "agricultural loophole" (Lesley, 2012) would help to make the U.S. compliant with international commitments and could have spillover effects to the broader international community.

higher demand for child labor and extend such resources to children who attend school at home. In most states, there is little incentive for children who experience child labor violations to report these violations because they may lose their job and, unlike other employment laws (e.g., those involving lost wages), the victims receive no compensation (Gerstein, 2024). As mandatory reporters, school social workers, teachers, and administrators would be obligated to report child labor violations if they became aware of them.

Addressing these issues could have far-reaching societal benefits—not only by helping school districts tackle enrollment and attendance challenges but also by fostering greater educational opportunities for vulnerable low-income and immigrant youth.

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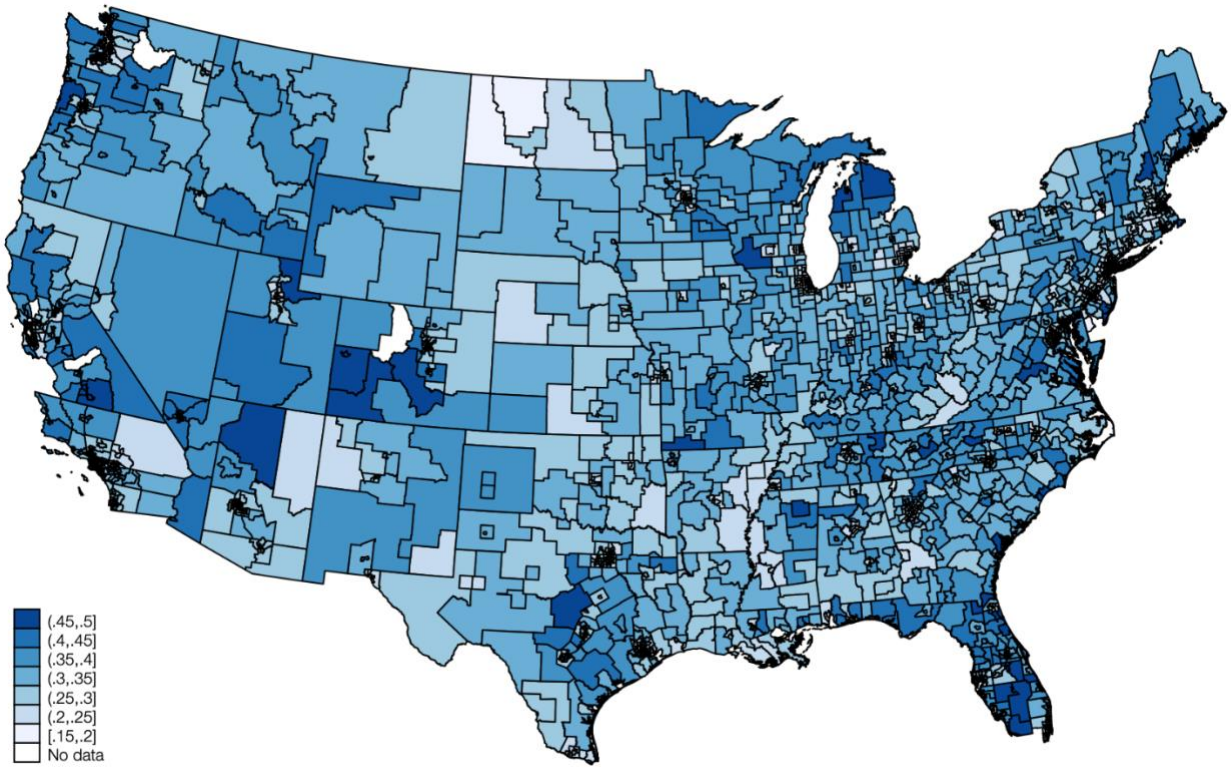
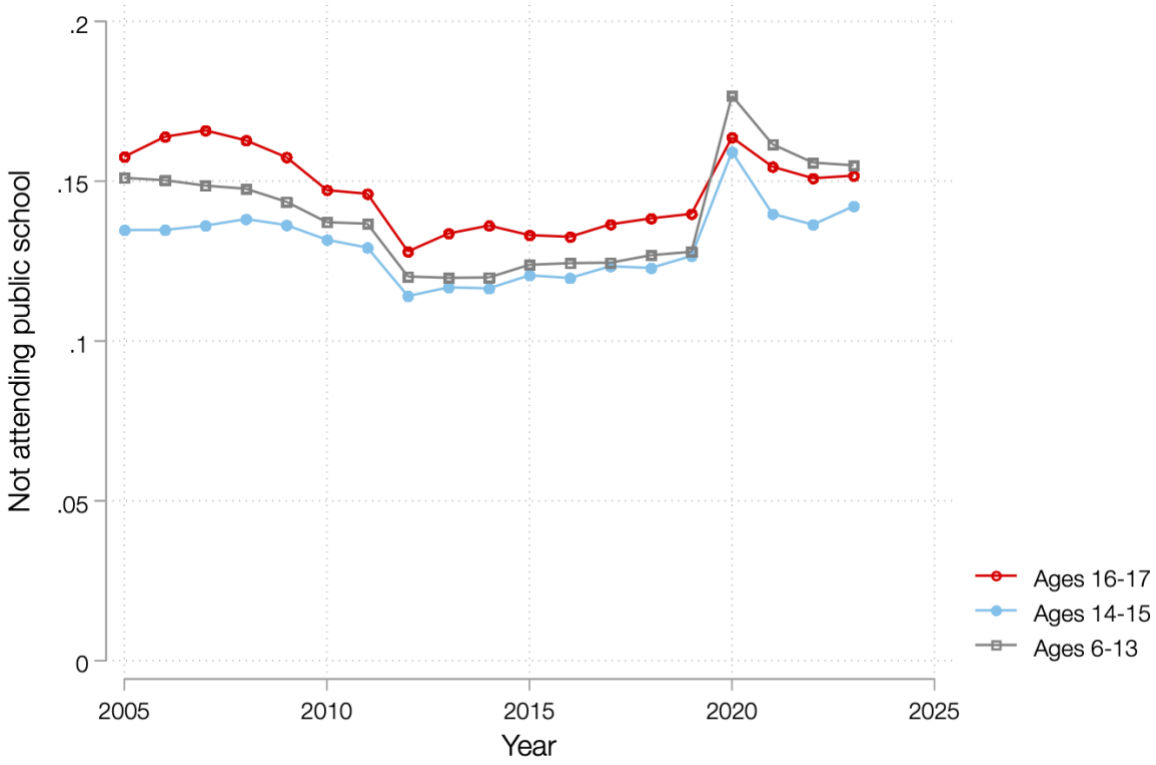
Tables and Figures

Figure 1. Average Share of Employment in High Child Labor Violation Industries by PUMA



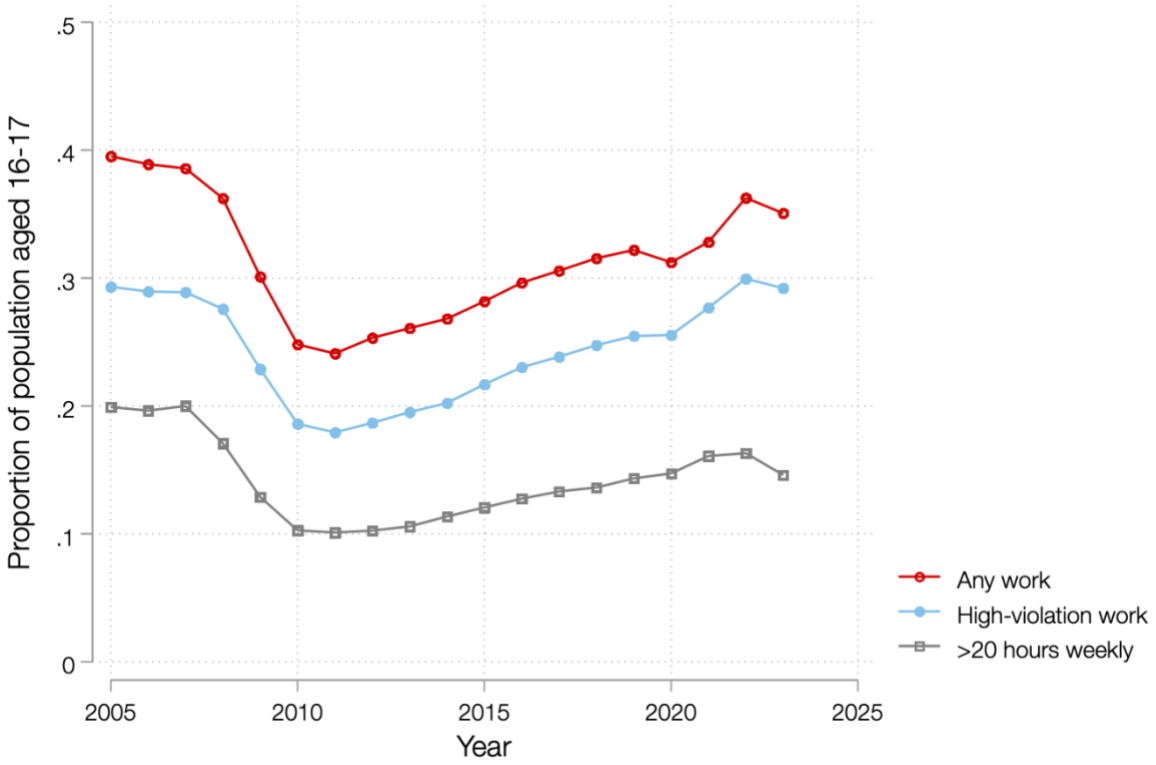
Note. The shading represents the average share of employment in each public use microdata area from 2005 to 2023 that is in high child labor violation industries, such that a 0 represents 0% high-violation industries and a 1 represents 100% high-violation industries. Hawaii and Alaska are not included in this descriptive map although they are included in the analysis.

Figure 2. Not Attending Public School by Age Group 2005 to 2023



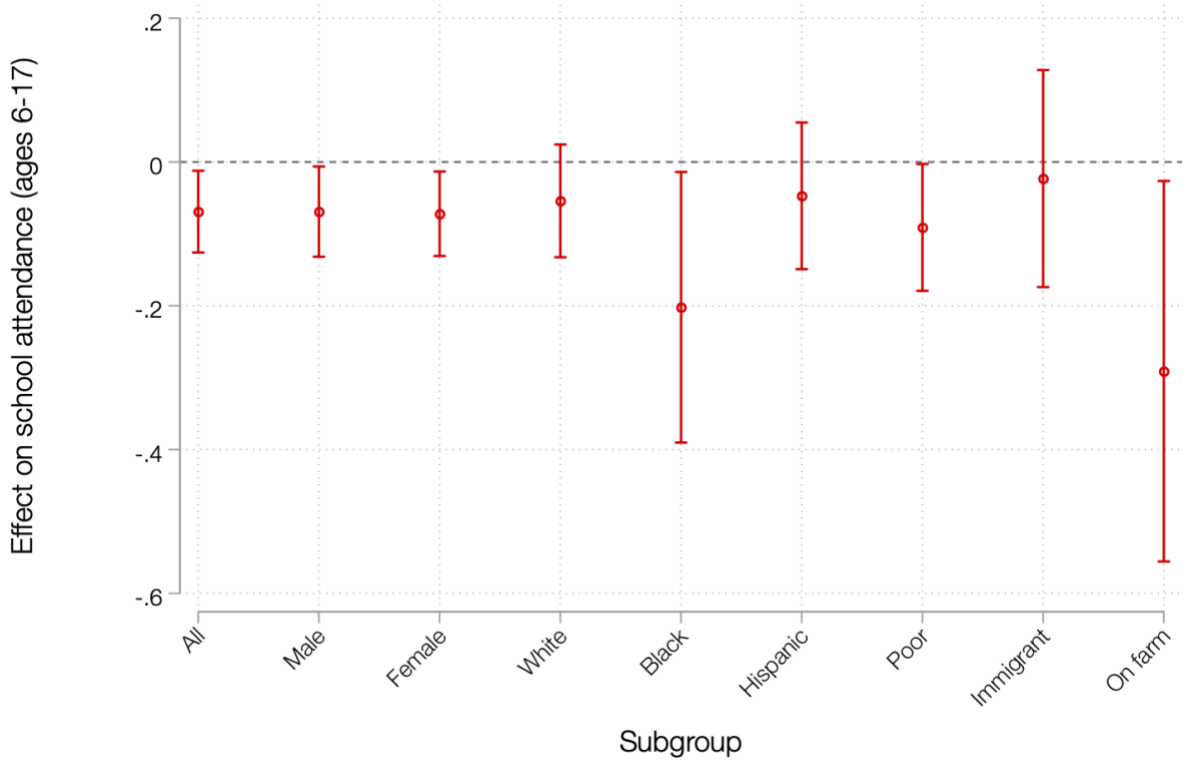
Note. Attendance is defined in the ACS as whether the child attended school at any time in the three months prior to the survey date. 0 refers to full attendance and 1 refers to full non-attendance. Those not attending public school could be in private school, home school, or no school. See Appendix Figure A5 for trends by school type.

Figure 3. Employment of Youth Aged 16-17 from 2005 to 2023



Note. This graph plots over time the proportion (0=0%, 1=100%) of youth aged 16 and 17 who are working at all, in a high-violation industry, and more than 20 hours weekly.

Figure 4. Effects of Local High-Violation Employment Share on School Attendance by Group



Note. This graph corresponds to the results in Appendix Table A4. Each point estimate is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the likelihood of attending school any time in the past three months for the particular subgroup. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. 95% confidence intervals are based on robust standard errors, clustered by PUMA. Control variables include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table 1. Descriptive Summary of U.S. PUMAs 2005 to 2023

Variable	Mean	SD	Source
Bartik share high-violation employment	0.318	0.083	QCEW, WHD
Share high-violation employment	0.288	0.072	QCEW, WHD
Any work (ages 16-17)	0.320	0.159	ACS
High-violation industry work (ages 16-17)	0.248	0.135	ACS, WHD
Usual weekly hours (ages 16-17 employed)	18.153	4.919	ACS
Over 20 hours weekly (ages 16-17 employed)	0.455	0.217	ACS
Any school attendance (ages 6-17)	0.974	0.021	ACS
Public school attendance (ages 6-17)	0.865	0.071	ACS
Private / home school attendance (ages 6-17)	0.109	0.068	ACS
Population (thousands)	129.162	27.695	SEER
Share population aged 6-17	0.158	0.020	SEER
Share Black among ages 6-17	0.153	0.146	SEER
Share Hispanic among ages 6-17	0.199	0.164	SEER
Share of children 5-17 in poverty	0.178	0.075	SAIPE
Median household income (thousands)	60.114	18.813	SAIPE
Local unemployment rate	5.985	2.590	LAUS
Percent foreign born (ages 6-17)	0.047	0.047	ACS
PUMAs	*2,461*		
Observations	*46,451*		

Note. QCEW = Quarterly Census of Employment and Wages; WHD = Wage and Hour Division of the U.S. Department of Labor; ACS = American Community Survey; SEER = Surveillance, Epidemiology, and End Results Program; SAIPE = Small Area Income and Poverty Estimates; and LAUS = Local Area Unemployment Statistics. QCEW, SEER, SAIPE, and LAUS variables are calculated at the county-year level and then aggregated to the PUMA-year level using Census population allocation weights. ACS variables are calculated as survey-weighted means at the PUMA-year level.

Table 2. Effects of Local Share of Employment in High Child Labor Violation Industries on School Attendance (IV)

Treatment	Full sample	Ages 16-17	Ages 14-15	Ages 6-13
	Outcome: public school attendance			
Local share high violation employment (10 p.p.)	-0.069*	-0.079*	-0.075+	-0.069*
	(0.029)	(0.038)	(0.042)	(0.029)
	Outcome: private or home school attendance			
Local share high violation employment (10 p.p.)	0.058*	0.036	0.060	0.064**
	(0.023)	(0.025)	(0.037)	(0.025)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	14.6	14.2	14.7	14.7
Observations	46,451	46,451	46,450	46,451

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the likelihood of attending school any time in the past three months from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

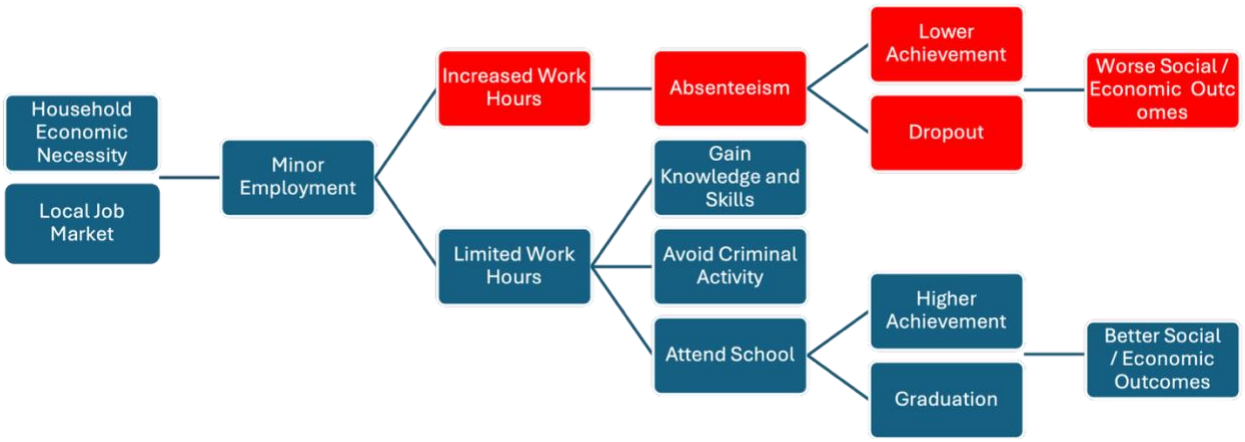
Table 3. Effects of Local Share of Employment in High Child Labor Violation Industries on Youth Employment (IV)

Treatment	Any work	High-violation work	Weekly hours	Over 20 hours weekly
Local share high violation employment (10 p.p.)	0.077+	0.077*	3.474*	0.129+
	(0.042)	(0.038)	(1.766)	(0.077)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	14.2	14.2	14.2	14.1
Observations	46,451	46,451	46,419	46,419

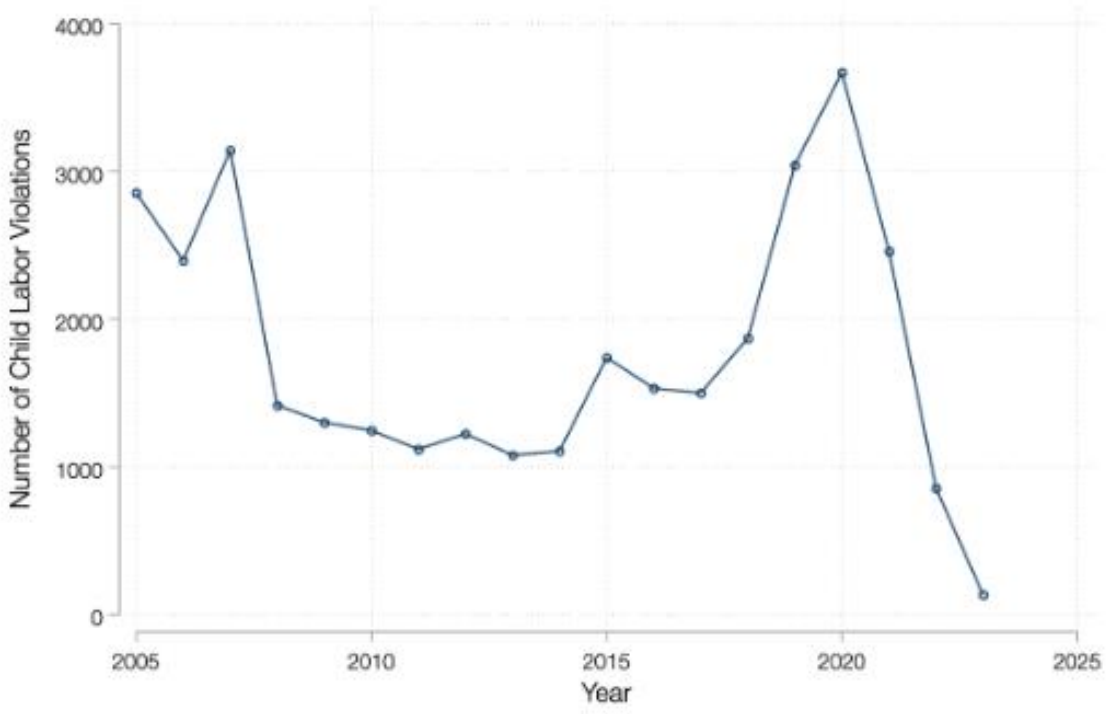
**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the employment outcomes for youth aged 16 to 17 from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Online Appendix. Additional Tables and Figures

Figure A1. Conceptual Framework of Youth Labor and Schooling

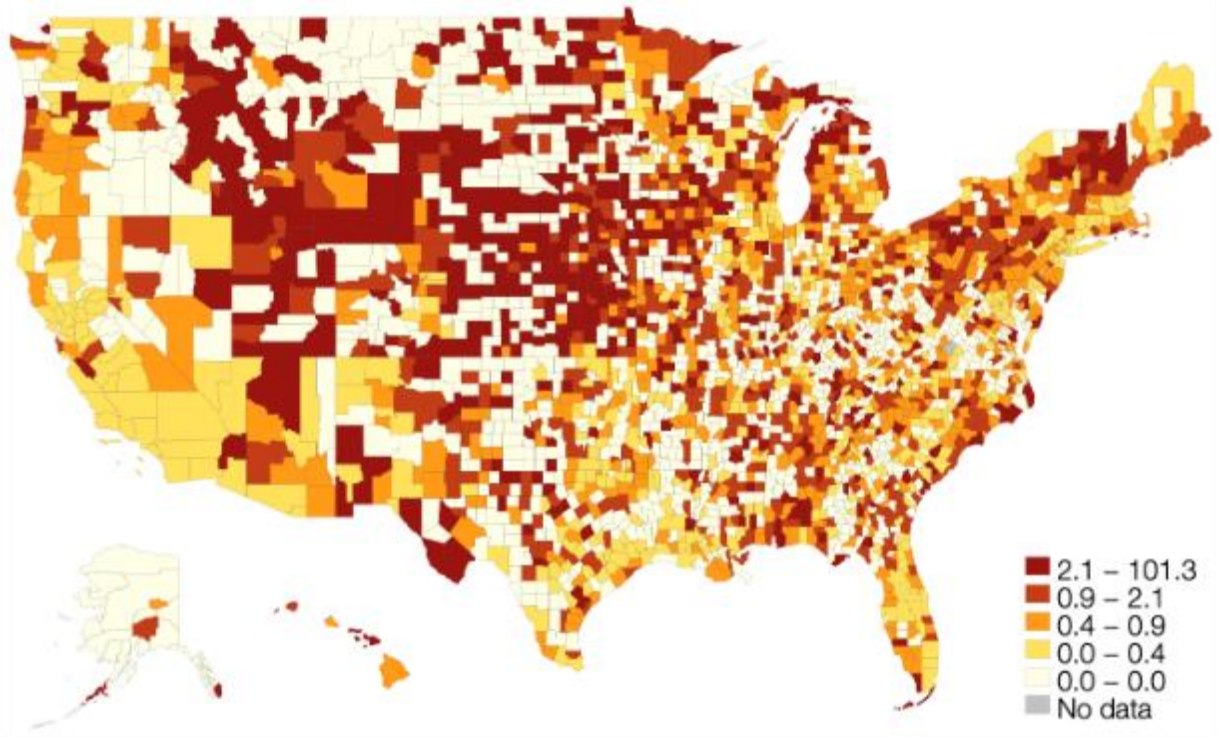


Appendix Figure A2. Number of Child Labor Violations by Year



Note. This graph tracks the number of cases with initial findings of child labor under FLSA occurring during each year. The number of cases in most recent years is an undercount because they are only entered into the database at the conclusion of the investigation; many cases post-2020 may not have been closed yet.

Figure A3. Number of Child Labor Violations Per 1,000 Children by County



Note. This map documents the number of reported child labor violations under FLSA from the U.S. Department of Labor Wage and Hour Division between 2005 and 2023 per 1,000 children aged 5-17 in that county.

Figure A4. Distribution of Shift-Share Measure of Local Employment in High-Violation Industries

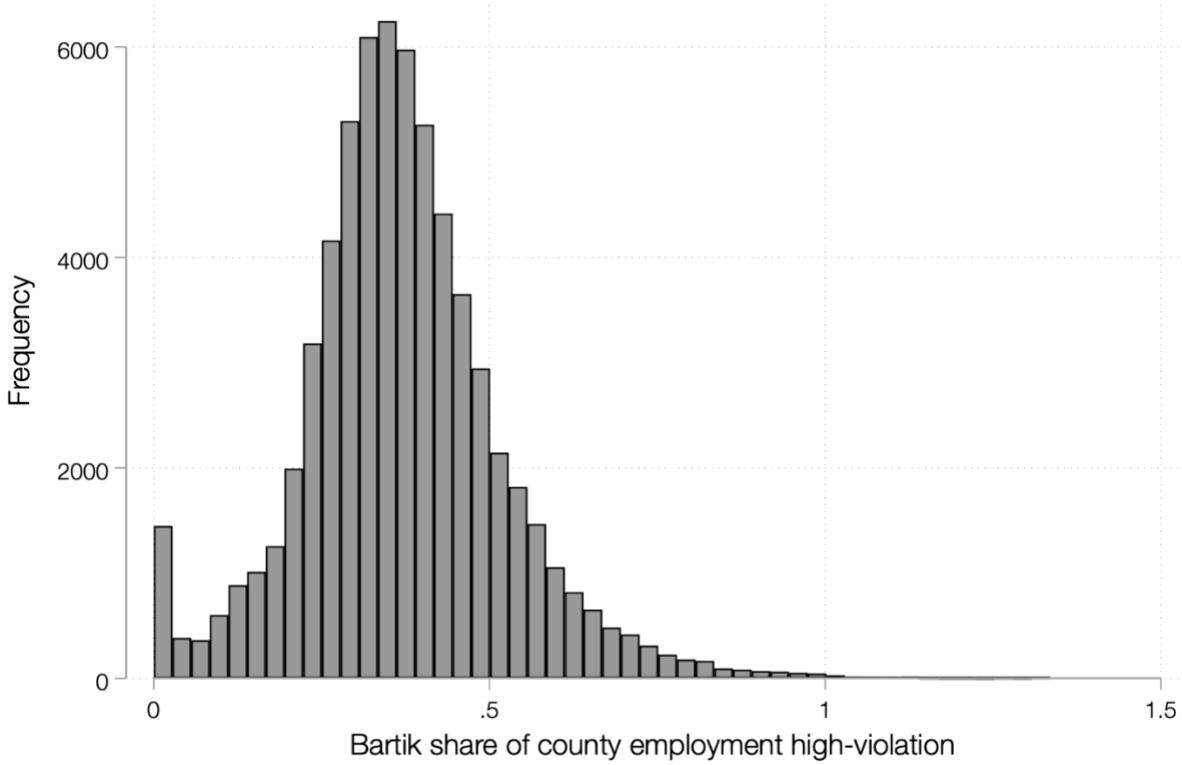
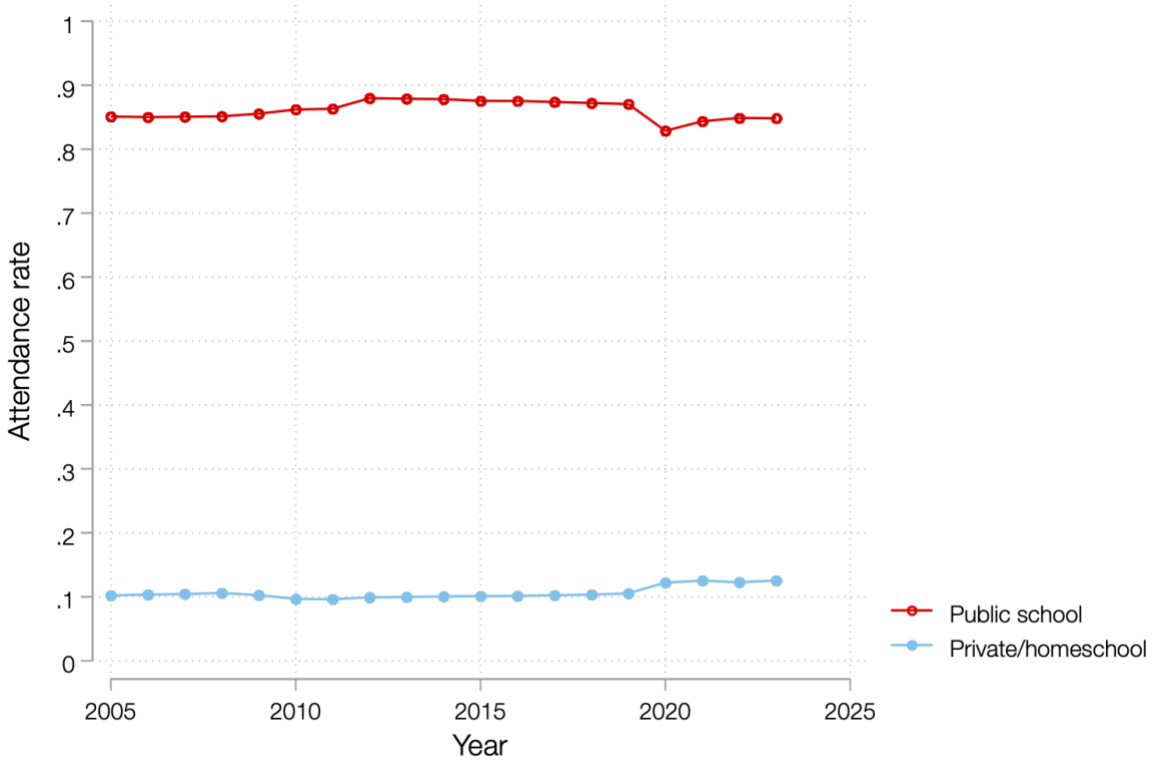
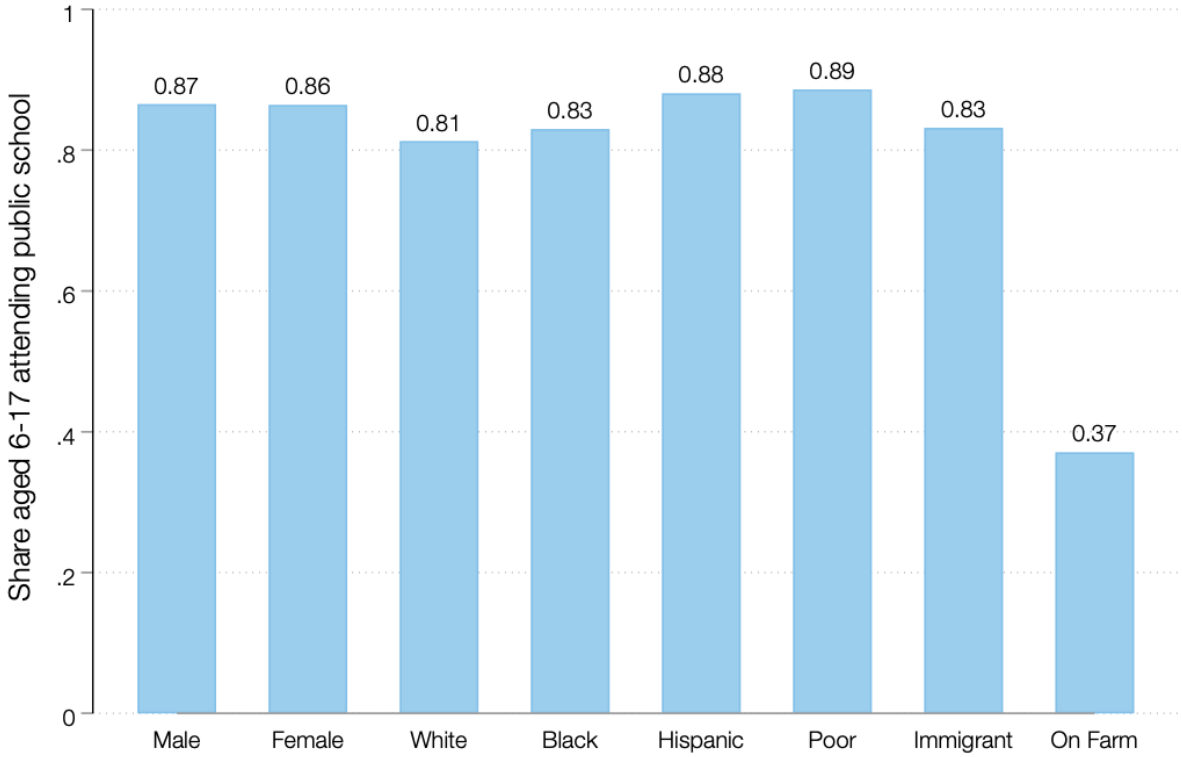


Figure A5. Attendance Rate by School Type 2005 to 2023



Note. Attendance is defined in the ACS as whether the child attended school at any time in the three months prior to the survey date. 1 refers to 100% attending that school type and 0 refers to 0% attending that school type.

Figure A6. Public School Attendance Rate by Subgroup 2005 to 2023



Note. This graph plots the percent of children aged 6 to 17 in each subgroup that attended public school sometime in the past three months. It does not include private or homeschool.

Table A1. List of High Child Labor Violation Industries

NAICS code	Industry description	Average employment	Violations per 10,000 employees	Minors in violation per 10,000 employees
7131	Amusement Parks and Arcades	184,288	4.384	3.722
4452	Specialty Food Stores	226,021	2.181	1.630
1112	Vegetable and melon farming	93,477	2.177	1.503
7221	Full-Service Restaurants	9,420,996	1.750	1.434
7139	Other Amusement and Recreation Industries	1,334,134	1.290	1.052
7111	Performing Arts Companies	115,417	1.200	1.118
5419	Other Professional, Scientific, and Technical Services	661,584	1.197	1.191
1113	Fruit and Tree Nut Farming	178,353	1.124	0.774
4451	Grocery Stores	2,605,411	0.893	0.709
5121	Motion Picture and Video Industries	367,536	0.877	0.809
3118	Bakeries and Tortilla Manufacturing	294,085	0.831	0.495
3219	Other Wood Product Manufacturing	239,292	0.637	0.263
5615	Travel Arrangement and Reservation Services	203,553	0.592	0.590
4922	Local Messengers and Local Delivery	78,196	0.575	0.544
3115	Dairy Product Manufacturing	139,974	0.543	0.414
3332	Industrial Machinery Manufacturing	115,384	0.507	0.165
4442	Lawn and Garden Equipment and Supplies Stores	151,415	0.502	0.314
1151	Support Activities for Crop Production	310,683	0.481	0.266
4539	Other Miscellaneous Store Retailers	329,176	0.463	0.345
4482	Shoe Stores	186,662	0.445	0.388
3211	Sawmills and Wood Preservation	95,270	0.399	0.152
7112	Spectator Sports	135,955	0.371	0.302
8133	Social Advocacy Organizations	210,221	0.357	0.186
4471	Gasoline Stations	889,850	0.333	0.221
2361	Residential Building Construction	776,949	0.328	0.150
5617	Services to Buildings and Dwellings	1,968,164	0.326	0.107
2123	Nonmetallic Mineral Mining and Quarrying	96,423	0.316	0.156
2381	Foundation, Structure, and Building Exterior Contractors	878,732	0.308	0.170
7211	Traveler Accommodation	1,817,877	0.294	0.229
2379	Other Heavy and Civil Engineering Construction	110,348	0.290	0.140
7223	Specialty Food Services	598,466	0.283	0.199
4543	Direct Selling Establishments	446,845	0.281	0.209
3116	Animal Slaughtering and Processing	504,915	0.269	0.123

8114	Personal and Household Goods Repair and Maintenance	75,321	0.266	0.212
4481	Clothing Stores	998,403	0.260	0.216
6233	Community Housing Services for the Elderly and Persons with Disabilities	813,575	0.246	0.240
2389	Other Specialty Trade Contractors	637,497	0.242	0.122
3119	Other Food Manufacturing	193,701	0.230	0.155
1114	Greenhouse, Nursery, and Floriculture Production	159,458	0.216	0.154
6231	Nursing Care Facilities	1,648,590	0.210	0.185
8111	Automotive Repair and Maintenance	899,122	0.206	0.145
4412	Other Motor Vehicle Dealers	153,589	0.202	0.124
4239	Other Miscellaneous Durable Goods Wholesalers	293,423	0.193	0.097
3121	Beverage Manufacturing	217,396	0.170	0.131
5611	Office Administrative Services	462,686	0.169	0.162
8123	Drycleaning and Laundry Services	299,072	0.164	0.117
1121	Cattle Ranching and Farming	144,477	0.163	0.107
5612	Facilities Support Services	145,629	0.161	0.151
4511	Sporting Goods, Hobby, and Musical Instrument Stores	482,689	0.152	0.118
3371	Furniture and Kitchen Cabinet Manufacturing	264,821	0.147	0.091

Note. High-violation industries were selected based on the following criteria: (1) The number of violations per employee was in the top quartile of all industries; (2) the number of minors in violation per employee was in the top quartile of all industries; and (3) the average employment from 2005 to 2023 was not in the bottom quartile of all industries. The numbers of minors in violation is typically lower than the number of violations in a given case because a single minor working can incur multiple violations.

Table A2. Effects of Bartik Shift-Share Instrument on Local Share of Employment in High Child Labor Violation Industries (First Stage)

Treatment	Observed share (10 p.p.)
Bartik share high violation employment (10 p.p.)	0.242** (0.063)
Control variables	Yes
PUMA fixed effect	Yes
Year fixed effect	Yes
Year x baseline share FE	Yes
First stage F-statistic	14.6
Observations	46,451

**p<0.01, *p<0.05, +p<0.1. This shows the estimated effect of an increase in the Bartik shift-share estimate of local employment in high violation industries on the observed local share of employment in high violation industries. Both measures are in 10 percentage point increments. Robust standard errors in parentheses, clustered by PUMA. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table A3. Falsification Check: Effects of Local Share of Employment in High Child Labor Violation Industries on PUMA Covariates

Treatment	Log pop	Percent age 6-17	Percent Black	Percent Hispanic	Percent poverty	Percent foreign
Local share high violation employment (10 p.p.)	1.202 (0.743)	0.014 (0.042)	0.519+ (0.278)	-0.047 (0.157)	0.117 (0.121)	0.198 (0.148)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes	Yes	Yes
First stage F-statistic	14.9	14.0	16.4	16.4	14.3	14.2
Observations	46,451	46,451	46,451	46,451	46,451	46,451

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on a PUMA demographic covariate from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population.

Table A4. Effects of Local Share of Employment in High Child Labor Violation Industries on Public School Attendance by Population Subgroups (IV)

Student population	Full sample	Ages 16-17	Ages 14-15	Ages 6-13
All	-0.069*	-0.079*	-0.075+	-0.069*
	(0.029)	(0.038)	(0.042)	(0.029)
Low income	-0.091*	-0.019	-0.109	-0.115*
	(0.045)	(0.075)	(0.076)	(0.051)
Immigrant	-0.023	-0.048	0.232	0.020
	(0.077)	(0.117)	(0.144)	(0.108)
Farm	-0.291*	-0.199+	-0.071	-0.214
	(0.135)	(0.110)	(0.103)	(0.135)
Male	-0.069*	-0.070+	-0.083	-0.073*
	(0.032)	(0.039)	(0.051)	(0.034)
Female	-0.072*	-0.067	-0.061	-0.069*
	(0.030)	(0.047)	(0.042)	(0.031)
White	-0.054	-0.155*	-0.028	-0.071
	(0.040)	(0.068)	(0.057)	(0.048)
Black	-0.202*	-0.046	-0.112	-0.177+
	(0.096)	(0.107)	(0.110)	(0.093)
Hispanic	-0.047	0.187+	0.032	-0.022
	(0.052)	(0.113)	(0.099)	(0.061)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on outcomes from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table A5. Effects of Local Share of Employment in High Child Labor Violation Industries on School Attendance (IV) - No Controls

Treatment	Full sample	Ages 16-17	Ages 14-15	Ages 6-13
	Outcome: public school attendance			
Local share high violation employment (10 p.p.)	-0.072*	-0.091*	-0.077+	-0.069*
	(0.031)	(0.041)	(0.044)	(0.030)
	Outcome: private or home school attendance			
Local share high violation employment (10 p.p.)	0.064*	0.044	0.064	0.070**
	(0.026)	(0.027)	(0.040)	(0.027)
Control variables	No	No	No	No
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	14.4	13.9	14.4	14.5
Observations	46,451	46,451	46,450	46,451

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the likelihood of attending school any time in the past three months from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population.

Table A6. Effects of Local Share of Employment in High Child Labor Violation Industries on Youth Employment (IV) – No Controls

Treatment	Any work	High-violation work	Weekly hours	Over 20 hours weekly
Local share high violation employment (10 p.p.)	0.134**	0.133**	5.132**	0.195*
	(0.048)	(0.045)	(1.981)	(0.085)
Control variables	No	No	No	No
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	13.9	13.9	13.8	13.8
Observations	46,451	46,451	46,419	46,419

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the employment outcomes for youth aged 16 to 17 from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Estimates weighted by PUMA school-aged population.

Table A7. Effects of Bartik Shift-Share of Local Employment in High Child Labor Violation Industries on School Attendance (Reduced Form)

Treatment	Full sample	Ages 16-17	Ages 14-15	Ages 6-13
	Outcome: public school attendance			
Bartik share high violation employment (10 p.p.)	-0.017**	-0.019**	-0.018*	-0.017**
	(0.005)	(0.006)	(0.008)	(0.006)
	Outcome: private or home school attendance			
Bartik share high violation employment (10 p.p.)	0.014**	0.009+	0.014+	0.016**
	(0.004)	(0.005)	(0.007)	(0.005)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	14.6	14.2	14.7	14.7
Observations	46,451	46,451	46,450	46,451

**p<0.01, *p<0.05, +p<0.1. Each cell is the estimated effect of a 10-percentage point increase in the Bartik local shift-share of employment in high child labor violation industries on the likelihood of attending school any time in the past three months from a separate regression. Robust standard errors in parentheses, clustered by PUMA. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table A8. Effects of Bartik Shift-Share of Local Employment in High Child Labor Violation Industries on Youth Employment (Reduced Form)

Treatment	Any work	High-violation work	Weekly hours	Over 20 hours weekly
Bartik share high violation employment (10 p.p.)	0.018*	0.018*	0.824*	0.031+
	(0.009)	(0.008)	(0.388)	(0.017)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
Observations	46,451	46,451	46,419	46,419

**p<0.01, *p<0.05, +p<0.1. Each cell is the estimated effect of a 10-percentage point increase in the Bartik local shift-share of employment in high child labor violation industries on the employment outcomes for youth aged 16 to 17 from a separate regression. Robust standard errors in parentheses, clustered by PUMA. Estimates weighted by PUMA school-aged population. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table A9. Effects of Local Share of Employment in High Child Labor Violation Industries on School Attendance (IV) – No Population Weights

Treatment	Full sample	Ages 16-17	Ages 14-15	Ages 6-13
	Outcome: public school attendance			
Local share high violation employment (10 p.p.)	-0.621*	-0.731*	-0.641+	-0.612*
	(0.246)	(0.345)	(0.340)	(0.254)
	Outcome: private or home school attendance			
Local share high violation employment (10 p.p.)	0.508*	0.327	0.466	0.575*
	(0.204)	(0.238)	(0.302)	(0.225)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
First stage F-statistic	14.6	14.2	14.7	14.7
Observations	46,451	46,451	46,450	46,451

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the likelihood of attending school any time in the past three months from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.

Table A10. Effects of Local Share of Employment in High Child Labor Violation Industries on Youth Employment (IV) – No Population Weights

Treatment	Any work	High-violation work	Weekly hours	Over 20 hours weekly
Bartik share high violation employment (10 p.p.)	0.067+	0.062+	3.543*	0.130+
	(0.040)	(0.036)	(1.648)	(0.072)
Control variables	Yes	Yes	Yes	Yes
PUMA fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Year x baseline share FE	Yes	Yes	Yes	Yes
Observations	46,451	46,451	46,419	46,419

**p<0.01, *p<0.05, +p<0.1. Each cell is the 2SLS estimated effect of a 10-percentage point increase in the local share of employment in high child labor violation industries on the employment outcomes for youth aged 16 to 17 from a separate regression. Robust standard errors in parentheses, clustered by PUMA. The instrumental variable is the Bartik shift-share estimate of the local share of employment in high child labor violation industries. Control variables in all models include: log population, share population aged 6-17, share of children aged 6-17 Black, share of children aged 6-17 Hispanic, share of children aged 5-17 in poverty, median household income, the local unemployment rate, and the share of children aged 6-17 foreign born.