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PROXIMITY TO ABORTION SERVICES AND CHILD MALTREATMENT

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ABSTRACT

This study provides a comprehensive analysis of the relationship between the accessibility of abortion services and incidences of child maltreatment across the United States, using data from the National Incident-Based Reporting System (NIBRS) and the Myers abortion facility database from 2011 to 2018. The analysis reveals that a rise in travel distance to the nearest abortion facility significantly increases the incidence of child maltreatment. Specifically, we find that a 100-mile increase in travel distance was associated with a 21.7% increase in maltreatment reports. This effect is particularly pronounced for very young children, non-White children, and those living in economically disadvantaged, racially diverse, and rural areas. Furthermore, supplemental analyses using data from the National Child Abuse and Neglect Data System (NCANDS) and county-level eviction records for renting households reveal economic stability and housing security as significant mediators linking barriers to abortion services to an increased risk of maltreatment. These findings contribute to a deeper understanding of the complex interplay between reproductive health services access, socio-economic factors, and child welfare.

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1. Introduction

Child maltreatment, which encompasses neglect, physical, emotional and sexual abuse, is a serious and prevalent societal problem in the United States. In 2022 alone, there were 558,899 child victims reported at a rate of 7.7 per 1,000 children in the population, and among those who are abused or neglected, an estimated 1,990 lives were lost (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2024). Particularly worrisome is the vulnerability of the youngest children. Of children who were maltreated, those under the age of one accounted for 14.7 percent of victims in 2022 – up from 12.7 percent in 2010 (U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children's Bureau, 2022, 2024). Furthermore, the economic burden of child maltreatment is staggering, with a total lifetime economic burden estimated at approximately $592 billion in 2018, making it as expensive as diseases like heart disease and diabetes (Klika, Rosenzweig, and Merrick, 2020; Centers for Disease Control and Prevention, 2022). Beyond the immediate harm, the consequences of child maltreatment at early stage could extend far into adulthood, adversely affecting psychological, behavioral, and physical health (Lansford et al., 2002; Fletcher, 2009; Herringa et al., 2013; Min et al., 2013; Danese and Widom, 2023). Aside from negative health effects, studies have documented a series of lifelong repercussions, including reduced employment and earnings (Currie and Spatz Widom, 2010), lower education levels (Currie and Spatz Widom, 2010; Henkhaus, 2022), increased rates of incarceration and crime (Currie and Tekin, 2012), and a higher likelihood of teen pregnancy (Anda et al., 2001). Moreover, maltreatment is more common in families of lower socioeconomic status, exacerbating disparities in the life chances of children from different backgrounds (Paxson and Waldfogel, 1999, 2002). Therefore, there is a critical need to understanding and addressing the factors and conditions that contribute to child maltreatment cannot be overstated.

In addition to well-established factors like parental stress (Warren and Font, 2015), substance overdose (Evans, Harris, and Kessler, 2022), and lack of social support (Bullinger and Boy, 2023; Austin et al., 2023), the availability of reproductive health services, particularly abortion services, may be a key determinant of child victimization, especially among infants. When financial and logistical barriers to abortion services rise, this can lead to an increase in the proportion of unwanted pregnancies being carried to term. The arrival of an unplanned child can impose significant emotional and financial stress on parents as they struggle to navigate the unanticipated responsibility of caring for a new life without adequate support or preparation.[1] This stress compounded by the

[1] Using data from the Turnaway Study, Biggs et al. (2017) demonstrate that being denied an abortion is associated with adverse psychological outcomes for women, including increased symptoms of anxiety,

intense needs of infants, who require constant care, can create challenging environments for infants, potentially leading to increased instances of child maltreatment (Bitler and Zavodny, 2002; Sen, 2007; Rocca et al., 2021; Miller, Wherry, and Foster, 2023). Furthermore, restrictive abortion policies may result in a disproportionate increase in births of "unwanted" children, particularly affecting young, single mothers and those from lower socioeconomic backgrounds (Sen, 2007; Eddelbuettel and Sassler, 2023). This suggests a basis for hypothesizing that children born to mothers facing a higher barrier to abortion access may encounter inferior outcomes compared to those born to mothers facing a lower barriers. The potential path from abortion access to child maltreatment has likely become more relevant in the wake of recent shifts in U.S. abortion policies, marked by more restrictive laws in several states, potentially resulting in a higher number of unwanted or unplanned births. The significance of this path is further amplified by the U.S. Supreme Court decision that overturned *Roe v. Wade* in 2022, ending the federally protected right to abortion upheld for decades. This landmark ruling may lead to further policy decisions that could worsen the already escalating barriers to abortion services, potentially resulting in a higher number of vulnerable children being born susceptible to maltreatment.

There exists a very limited body of literature focusing on the effects of abortion access or restrictions on child welfare outcomes. Bitler and Zavodny (2002, 2004) found evidence of a decrease in child maltreatment following abortion legalization and less restrictive access to abortion services using state-level data on measures of maltreatment. Their analysis considered various measures of abortion access, including Medicaid funding restrictions, parental involvement laws mandating notification or consent for minors, and mandatory delay laws. Adkins et al. (2024) investigated the relationship between the number of children entering foster care at the state level and Targeted Regulation of Abortion Providers (TRAP) laws.[2] Their findings indicate a significant increase in foster care placements after abortion access was restricted in states with TRAP laws compared to states without such laws. Sen (2007) documented that state-level restrictions on abortion access, such as enforced parental consent and notification laws, absence of public funding, and mandatory delays, were significantly associated with higher rates of fatal injuries among children, particularly affecting white children.

Our study extends the existing literature by centering on the proximity to the

lower self-esteem, and reduced life satisfaction. Additionally, Miller, Wherry, and Foster (2023) connect credit report data to the Turnaway Study and find that women denied an abortion experience substantial increases in financial distress.

[2]TARP laws are primarily politically motivated and target the restriction of abortion access by imposing various building and clinical requirements on providers. Adkins et al. (2024) examine four types of TARP laws, including building regulations mandating abortion facilities to adhere to standards similar to ambulatory service centers, transfer agreements requiring clinics to have arrangements with local hospitals, admitting privilege laws necessitating abortion providers to have admitting privileges at nearby hospitals, and distance requirements mandating that abortion clinics be situated within a specified distance from a hospital.

nearest abortion facility as a metric for assessing barriers to abortion. Specifically, we extracted reported child maltreatment incidents by police agencies from the National Incident-Based Reporting System (NIBRS) between 2011 and 2018, and linked them to a novel database on travel distance to the nearest abortion facility, as constructed by Myers (2024). This measure offers several distinct advantages over solely examining abortion laws. First, it provides a more precise measurement of access, capturing real-world barriers beyond the legal framework. This approach allows for a nuanced understanding of accessibility, recognizing that geographic and transportation challenges can vary significantly within the same legal context. Additionally, travel distance is closely linked to socioeconomic factors, offering insights into how access disparities affect different population segments. Unlike static legal measures, travel distance is sensitive to temporal changes, such as clinic closures or openings, providing a dynamic perspective on access over time. This measure also has broader applicability across various legal contexts, making the findings more generalizable. Importantly, focusing on travel distance can yield direct policy implications, highlighting specific areas where interventions can improve access to abortion services. Another notable aspect of our study is that we perform our primary analysis at the county level, whereas previous studies have exclusively focused on state-level measures. Lastly, our study concentrates on the time period spanning 2011 to 2018, during which the operation of abortion service facilities faced escalating challenges, resulting in numerous closures and subsequently imposing significant increases in travel distances required to access abortion services for a substantial portion of women in the United States. In contrast, previous studies utilized data from more distant periods. For instance, Sen (2007) examined the period from 1981 to 2002, while Bitler and Zavodny (2002, 2004) use data from 1976 to 1996.

A further strength of our analysis stems from the use of multiple datasets in a unified framework. In addition to NIBRS, we use Child Files from the National Child Abuse and Neglect Data System (NCANDS) between 2011 and 2018. These files consist of case-specific information on investigations into alleged or substantiated cases of child maltreatment, including demographics of children and perpetrators, and potential risk factors for caregivers. The caregiver risk factors include categories such as domestic violence, inadequate housing, financial instability, reliance on public assistance, and substance abuse issues. Such data have the potential to offer invaluable insights into the underlying mechanisms linking abortion proximity to occurrences of maltreatment.

Finally, we use data on eviction filings among renting households at the county level from 2011 to 2018, obtained from Gromis et al. (2022). This dataset aggregates over 73 million individual eviction records at the county level. Financial strain resulting from an unplanned pregnancy carried to term is a likely mechanism linking barriers to abortion services to an increased risk of maltreatment. Eviction, as a primary indicator of financial strain, offers crucial insights into the potential mediating role of economic factors in the relationship under study.

Our empirical analyses reveal a sizeable positive effect of increased barriers to reproductive health service on the rate of child maltreatment. This effect is most pronounced among children no more than 1 year old, with a 21.7% increase in maltreatment report associated with every 100-mile increase in travel distance to the nearest abortion facility. As expected, the effect is minimal among children older than 2. The lack of such an association in older children, who would have been born before such changes in access, serves as a conceptual placebo test, providing further credence to our hypothesis. It indicates that the observed associations are more likely a result of the conditions surrounding the birth and infancy period rather than an artifact of the broader social or environmental factors, mitigating the potential confounding influence of wider social factors.

Our findings reveal clear racial disparities in how increased travel distances to abortion services affect child maltreatment rates. Specifically, we observed that non-White infants are disproportionately impacted by greater travel distances compared to their non-Hispanic white counterparts. This finding is congruent with Adkins et al. (2024), which documented heightened risks for foster care entry among racial or ethnic minority children following the enactment of TRAP laws. The pronounced effect on non-White infants may stem from a confluence of structural inequities that disproportionately affect minority communities. These include, but are not limited to, historical segregation in healthcare provision, economic disenfranchisement, and differential access to social services. Such systemic issues are exacerbated in the context of reproductive healthcare, where racial disparities are well-documented. The stressors associated with unplanned pregnancies may be particularly acute in these communities, where there are often fewer resources to buffer the economic and social challenges of early parenthood. Consistent with this hypothesis, we also find evidence of increased eviction filings as proximity to abortion services increases. This effect is more pronounced in counties with a relatively higher proportion of the childbearing female population, as well as those with above-median poverty rates and rural populations.

2. Data

2.1. Child Maltreatment

We draw child maltreatment data from the National Incident-Based Reporting System (NIBRS). As the national standard for law enforcement crime data reporting in the U.S., NIBRS offers detailed and high-quality information crucial for accurately comprehending victimization and offending behavior. It captures comprehensive details about the characteristics of each crime incident, including a broad array of offenses (simple assault, aggravated assault, rape, murder, etc.), along with demographic information about victims, offenders, and arrestees. However, the non-mandatory participation in NIBRS introduces a limitation due to the inconsistency in reporting across agencies. To address this issue, we follow the method of existing studies and limit our analysis to agencies that have reported consistently throughout the year (see, e.g., Bondurant, Lindo, and Swensen 2018). This method results in an unbalanced agency-year panel data, with sample size varies by year, as Table A1 shows. We use Kaplan (2021)'s concatenated NIBRS data for years between 2011 and 2018. Our final sample includes child maltreatment data from 6,104 police agencies across 1,708 counties in 41 states, offering a granular view of maltreatment incidents at the agency level.

Following Block and Kaplan (2022), we examine information about victims and offenders, the nature of their relationship as recorded by the police at the time of the report, and the occurrence of injuries to detect child maltreatment cases. Specifically, we concentrate on cases involving victims younger than 18 years. Furthermore, we require the offender to be the victim's biological parent, a stepparent, or the significant other of the biological parent, refining our criteria for identifying child maltreatment instances.

In our baseline analysis, we focus on child maltreatment among children of 1 year old or below. We use data on child maltreatment among children in other age ranges for placebo tests. Once we define the relevant age group and relationship categories, about 75% of offenses against children of one year old or younger pertain to simple and aggravated assault, which are considered physical abuse. Remaining offense types, such as sexual assault, rape, fondling, kidnapping, and murder account for 25% of our sample.

We supplement our analysis with data from the National Child Abuse and Neglect Data System (NCANDS) Child Files for the years 2013 through 2018.[3] These files contain reports of alleged child abuse and neglect that received a response from Child Protective Services (CPS). We secure access to these reports through a restricted data agreement with the National Data Archive on Child Abuse and Neglect. Similar to NIBRS, state reporting of maltreatment cases in the NCANDS Child Files is also voluntary; however, most states have consistently reported during our sample period.

We aggregate case-level data to county-level measures of child maltreatment, following the approach outlined in Evans, Harris, and Kessler (2022). In our aggregation process, if cases appear multiple times in different Child Files, we exploit the data reported in the most recent fiscal year, adhering to the recommendations in the NCANDS User's Guides. For each case, we determine the calendar year when the suspected maltreatment was initially reported to the state CPS agency, distinguishing it from the fiscal year when the case was resolved.[4] Furthermore, we only include counties that consistently appear

[3]Although we obtained NCANDS data going back to 2011, our effective sample period is from 2013 to 2018 due to changes in reporting standards in Florida and Idaho after 2012.

[4]Evans, Harris, and Kessler (2022) highlight that approximately 98% of cases are resolved within two years of their initial report. In our sample, 99.86% of the cases are unique, appearing only once in

in every Child File throughout our sample period.

Importantly, NCANDS data enable us to capture not only physical and sexual abuse cases, which collectively account for more than 17% of cases on average, but also child neglect, which comprises more than 75% of cases on average. Additionally, we are able to distinguish between alleged and substantiated child maltreatment cases and observe changes in child maltreatment by caregiver risk factors. We are particularly interested in examining whether the effects of increased travel distance are more pronounced in families where the caregiver initially has financial problems, receives social assistance, or has a history of addiction, mental health issues, and domestic violence.

Our objective is to integrate data from both NIBRS and NCANDS into a unified framework, allowing a comprehensive analysis of child maltreatment as travel distance to the nearest abortion facility increases. Specifically, we examine how increased travel distances affect a broad spectrum of child maltreatment cases.

2.2. Travel Distance to the Nearest Abortion Facility

We obtain the travel distance data from a novel database constructed by Myers (2024), hereafter referred to as the Myers database. This database is a product of an extensive and meticulous data compilation effort, leveraging a wide range of sources such as state licensing databases, current and historical facility websites, Planned Parenthood health center directories, National Abortion Federation (NAF) lists, and media reports. Its objective is to provide comprehensive coverage of all abortion service providers, including private physician offices, hospitals, and standalone clinics.[5] The Myers database calculates monthly travel distances for each county in the continental United States to their nearest abortion provider, using the geographical centroids of the counties as reference points. It offers a comprehensive county-by-month panel, showcasing the average travel distance to the nearest abortion facility from January 1, 2009, to May 1, 2023, and continues to be updated as new data become available.

To ensure compatibility with the child maltreatment data, we use the Myers dataset for the years 2010 to 2017.[6] We then aggregate the travel distance data into a county-by-year format to provide an annualized average travel distance for each county. Subsequently, we merge the annual travel distance data from the preceding year with NIBRS and NCANDS data using the county identifier.

the database.

[5]In other words, the Myers database includes all publicly-identifiable abortion facilities, excluding only those that perform a small number of abortions and do not advertise their services. For a direct comparison of the Myers database with existing sources on abortion facilities, such as those from the Guttmacher Institute or Advancing New Standards in Reproductive Health, see Myers (2024).

[6]We use travel distance from period t and child maltreatment from period $t + 1$, as the timing of abortion access is likely to impact births and, subsequently, child maltreatment in the next period.

2.3. Eviction Case Filings

The county-level data on eviction case filings is sourced from the Eviction Lab at Princeton University (Gromis et al., 2022). This database compiles more than 99 million individual eviction records from 48 states and the District of Columbia, including 73.2 million records purchased from LexisNexis Risk Solutions. These proprietary data were compiled through electronic requests for court records or manual reviews of courthouse files. The legal eviction process begins with the filing of an eviction lawsuit and can lead to various outcomes, ranging from uncontested tenant departures to court-mandated evictions, or resolutions that allow tenants to remain. This process, typically spanning several months, often generates multiple legal event records for each case. Gromis et al. (2022) aggregate these individual eviction records to the case level using probabilistic (inexact) matching of tenant names and addresses, and excludes filings against commercial properties. In our study, we use their data on eviction case filings from 2011 to 2018, which includes variables such as the number of eviction case filings and the total number of households renting properties in a county.

Our objective is to explore the potential financial strain caused by unplanned or unwanted births, which may result from increased travel distances to the nearest abortion facility. We aim to do this by examining changes in eviction case filings.

2.4. Other Covariates

We supplement our analytical data with various county and state characteristics to provide a more nuanced analysis. At the county level, we integrate demographic and socio-economic factors. Specifically, the proportion of white females aged 15 to 44 and the percentage of children under 17 are derived from the Surveillance, Epidemiology, and End Results (SEER) Program. Median household income information comes from the U.S. Census Bureau's Small Area Income and Poverty Estimates (SAIPE). The unemployment rate is sourced from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS). Additionally, the number of psychiatric treatment facilities is calculated using data from the U.S. Census Bureau's County Business Patterns.[7]

Earlier studies suggest that congestion at remaining facilities may limit access to abortion services (see, e.g., Lindo et al. 2020). In such cases, any potential effect could be driven by increased congestion rather than increased travel distance. To account for this possibility, we control for the "average service population" in the service region of each county and the number of abortion facilities in the destination county, as documented in the Myers database.[8]

[7]Although there is no previous evidence to suggest that healthcare providers who stop offering abortion services also cease providing other services like mental health treatment, we still aim to account for this possibility. We do so by controlling for the number of psychiatric treatment facilities.

[8]The average service population essentially measures the number of women aged 15-44 served per

On the state level, our dataset includes legislative and policy variables that could influence abortion access. We source data on mandatory abortion waiting periods from Myers (2021) and obtain information on parental involvement laws from Myers (2022). We also include economic support indicators, such as minimum wage and Earned Income Tax Credit (EITC) refund statuses, derived from the UKCPR National Welfare Data (UKCPR, 2023). In our most conservative specification, we nonparametrically control these policy changes by including state-by-year fixed effects.

2.5. Descriptive Evidence

Our final analytical sample consists of 38,827 agency-year observations. The average child maltreatment among children under or equal to 1 year old is 16.90 per 100,000 population, with a standard deviation of 83.13. Notably, about 75% of the observations have zero child maltreatment incidence. Figure A1 displays a histogram of the travel distance for counties throughout our study period. The average travel distance is 79 miles, with a median of 63 miles. The distribution is right-skewed, with the longest travel distance approaching 400 miles.

The top panel of Figure 1 visually depicts the geographical changes in travel distance to the nearest abortion facility from 2010 to 2017 in our final analytical sample. A considerable number of counties, particularly in states such as North Dakota (ND), South Dakota (SD), Montana (MT), Idaho (ID), Oklahoma (OK), and Maine (ME), have seen decreases in travel distances. The most notable reduction occurred in Kansas (KS), where the travel distance was reduced by more than 100 miles. This substantial decrease can be attributed to the reopening of Trust Women in 2013, following a closure period of four years due to the tragic murder of its founder. Other abortion clinic openings can be attributed to the increase in advanced practice clinicians who provide abortion services, as seen in Colorado (CO), and to the expanded telemedicine provision of abortion services, as in Maine (ME). Due to supply-side restrictions, notably the "Targeted Regulation of Abortion Providers" (TRAP) laws, there has been a discernible increase in travel distances to access abortion services in several states, including Texas (TX), Wisconsin (WI), Michigan (MI), and Ohio (OH). These legislative measures, which impose stringent requirements on abortion providers, have contributed to the closure of numerous facilities or have substantially limited their operational capacity, thereby escalating the travel distance for many individuals seeking abortion services in these states.

The bottom panel of Figure 1 displays the correlation between change in child maltreatment among children of 1 year old or below against changes in travel distance in our study period. This figure sheds several important insights: notably, an increase

clinic in a region (Lindo et al., 2020). The number of abortion facilities in the destination county is a categorical variable taking values of 1, . . . , 6-10, 11-15, 16-20, and 21+.

in travel distance is associated with a corresponding rise in child maltreatment cases. Specifically, counties that witnessed an increase in travel distance of less than 50 miles saw child maltreatment rates surge by 32.41%, whereas those experiencing an increase of 50 miles or more observed a 94.01% rise in maltreatment incidents. Furthermore, the figure suggests a monotonic relationship between the growth in travel distance and the incidence of child maltreatment, indicating that as the difficulty of accessing abortion services increases, the incidence of child maltreatment in the affected regions not only increases but does so in a significantly pronounced manner.

3. Empirical Approach

We exploit variations in travel distance to the nearest abortion facility across counties and over time in a difference-in-differences (DID) research design. In our analysis, we use a Poisson regression model, suitable for addressing the discrete nature of child maltreatment incidences, which can occasionally be zero. Since our child maltreatment data is aggregated at the agency level, we estimate the number of children under 17 served by each agency. To do so, we multiply the overall population covered by each agency by the percentage of the county's population that is under 17 years old. This population measure serves as the exposure variable in the following Poisson regression model:

$$E(Y_{a,c,s,t+1}|distance_{c,s,t}, X_{c,s,t}, \gamma_c, \gamma_t) = exp[f(distance_{c,s,t}) + \beta X_{c,s,t} + \gamma_c + \gamma_t + \gamma_{s,t}], \quad (1)$$

where $Y_{a,c,s,t+1}$ represents the incidence of reported child maltreatment by agency a in county c, state s, for the year $t+1$. Our treatment variable, $Distance_{c,s,t}$, quantifies the travel distance to the nearest abortion facility, reflecting the minimum distance a resident of county c, state s, must travel to access abortion services in year t. This distance measure serves as a proxy for the accessibility of abortion services, with longer distances signifying considerable barriers. To ensure flexibility in functional form, we model the distance to abortion facilities in various forms - linear, quadratic, and categorized - within our regression framework.

To mitigate the impact of potential unobserved confounding factors, we adjust for various county characteristics and state policy measures, as described in our data section. Our regression further includes county fixed effects, γ_c, and year fixed effects, γ_t, to control for time-invariant agency characteristics and common temporal shocks across counties, respectively. Our most comprehensive specification addresses unobserved factors varying across states and over time through the inclusion of state-by-year fixed effects. We cluster standard errors at the county level to accommodate for intra-county correlation among agencies and weight the agency-level analyses according to their respective population sizes.

In a continuous treatment setting, the identifying assumptions depend on the causal parameter of interest. We are primarily focused on estimating the average *level treatment effects*, which can be identified under the standard parallel trends assumption. Level treatment effects measure the difference between potential outcomes of counties experiencing increases in travel distance by d and those of untreated counties, where $d = 0$. In simpler terms, under the parallel trends assumption, we can determine whether there is a positive level treatment effect, i.e., whether increases in travel distance lead to an increase in the number of child maltreatment cases. After defining the causal parameter of interest and its identifying assumption, the next relevant question relates to the estimation process, particularly the justification for the estimator being used. Essentially, the level treatment effects, $Y_t(d) - Y_t(0)$, could be estimated by converting the treatment variable into a binary variable and employing a binary DID approach. In our event study, we compare counties that experience an increase in travel distance of at least one mile to untreated counties by leveraging a heterogeneity-robust estimator developed by Callaway and Sant'Anna (2021). This approach addresses concerns about potential bias arising from heterogeneous treatment effects in the two-way fixed effects (TWFE) regressions.

In addition to the level treatment effects, one may be inclined to identify the travel distance that generates the largest increase in child maltreatment cases. Callaway, Goodman-Bacon, and Sant'Anna (2024) define this causal parameter of interest as the average *causal response*, which illustrates how potential outcomes change with a marginal increase in d - that is, travel distance. The average causal response is essentially the slope of the ATT function, $Y_t'(d)$. As illustrated by Callaway, Goodman-Bacon, and Sant'Anna (2024), we need a stronger version of the parallel trends assumption to identify the causal effect of a small change in the "dose," which is described as follows:

$$\begin{aligned} &E(Y_{a,c,s,t+1}(d) - Y_{a,c,s,t}(0)|X_{c,s,t}, \gamma_c, \gamma_t) \\ &\qquad = E(Y_{a,c,s,t+1}(d) - Y_{a,c,s,t}(0)|X_{c,s,t}, \gamma_c, \gamma_t, distance_{c,s,t} = d) \quad \text{for any } d \geq 0. \end{aligned} \tag{2}$$

This assumption posits that, conditional on the characteristics in $X_{c,s,t}$, the expected evolution of child maltreatment across all counties — if each had experienced a travel distance of d — would mirror the actual evolution observed in counties with that specific travel distance. In other words, the strong parallel trends assumption limits treatment effect heterogeneity, suggesting that different dose groups (e.g., low vs. high travel distance counties) should not experience varying treatment effects from the same dose, d.

The causal response decomposition of the TWFE estimate in Callaway, Goodman-Bacon, and Sant'Anna (2024) show that, despite having positive weights that also integrate to one, heterogeneity bias contaminates the estimates. This bias term disappears under the strong parallel trends assumption. For instance, if high travel distance counties experience a larger increase in child maltreatment at every dose, then the TWFE estimate would be biased upward. In our analysis, we later estimate nonlinear effects and find that, if anything, high-dose groups experience smaller increases in child maltreatment compared to low-dose groups. Therefore, it may be plausible to consider the TWFE estimates in Equation (1) as a lower bound, especially in a policy context where one is interested in the impact of marginal increases in travel distance to the nearest abortion facility.

Alternatively, one might address dose heterogeneity by considering functional form assumptions related to travel distance. Although we are hesitant to adopt stringent functional form assumptions, as previously mentioned, we do verify the robustness of our estimates through various parametric estimation strategies that incorporate different functional forms for the dose. Importantly, following a strategy similar to the one suggested by Callaway, Goodman-Bacon, and Sant'Anna (2024), we saturate the model by including categorical measures of travel distance and applying nonparametric estimation techniques in alternative regression specifications. These nonparametric methods may be particularly appealing to researchers seeking to overcome the limitations of TWFE without resorting to parametric functional form constraints.

4. Results

We present our benchmark results on the impact of travel distance to the nearest abortion facility on child maltreatment in Table 1. As previously mentioned, our analysis uses a flexible approach regarding the functional form of travel distance, exploring both linear and nonlinear effects. In alternative specifications, we further control for state-by-year fixed effects, leveraging variations in changes in abortion facility distance across counties within a state in a given year.

Using a linear distance measure, we find that a 100-mile increase in the distance to the nearest abortion facility increases child maltreatment by approximately 21.7% ($p < 0.05$) as shown in column (1).[9] The inclusion of state-by-year fixed effects in column (2) yields qualitatively similar results. In column (3), we explore the nonlinear effects of abortion facility distance by including a quadratic term. Our findings suggest a hump-shaped relationship between abortion facility distance and child maltreatment. This pattern remains consistent when we classify travel distances into ordered ranges (i.e., 50-100 miles, 100-150 miles, 150-200 miles, and 200+ miles). This method relaxes the constraints of the parametric functional form by employing a nonparametric approach. Notably, in column (6), our most comprehensive specification reveals a pronounced hump-shaped pattern,

[9]We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

indicating that while child maltreatment increases with distance, the rate of increase diminishes after 200 miles.

In Appendix Figure A2, we visually illustrate these nonlinear trends by considering various baseline travel distances. Specifically, we plot the effects of distance to the nearest abortion facility on child maltreatment from baseline distances of 0 miles, 63 miles (median), and 79 miles (mean). The graphs clearly show a nonlinear relationship, where the magnitude of change in child maltreatment decreases as the baseline travel distance increases. For instance, an increase of 100 miles from a baseline of 0 miles results in a 105.2% increase in child maltreatment, while the same increase from baselines of 63 and 79 miles leads to increases of 41.6% and 28.9%, respectively. These findings further support our earlier assertion that high-dose groups (as opposed to low-dose groups) experience smaller increases in child maltreatment at every dose, likely alleviating concerns about overestimation. Additionally, these findings are consistent with prior research that documents diminishing marginal effects of increased travel distances on abortion and birth rates (Fischer, Royer, and White, 2018; Lindo et al., 2020; Venator and Fletcher, 2021; Myers, 2024).

Threats to identification. In our benchmark analysis, we control for state-by-year fixed effects to account for potential state policy changes or economic shocks that vary over time and may correlate with our measures of distance to abortion facilities and instances of child maltreatment. This approach allows us to exploit within-state variations at specific times. While the robustness of our findings under these specifications is reassuring, we conduct additional robustness checks to address potential endogeneity concerns. A particular concern is the possibility that abortion facility closures - and hence increased travel distances - are endogenously driven by county abortion rates. To test this reverse feedback effect, we regress our treatment variable, the travel distance to the nearest abortion facility in period $t+1$, against the abortion rate in period t. If the travel distance is indeed endogenous to the abortion rate, we would anticipate finding a statistically significant relationship. However, as shown in Table A2, we find no evidence to support this, with one exception. There is a single marginally significant estimate in column (2), but even this result carries a negative sign, contradicting the hypothesis that restrictive reproductive policies - intended to lead to facility closures and increased travel distances - are driven by increases in abortion rates.

In a similar manner, we address another concern - whether counties experiencing changes in the distance to abortion facilities may differ from those without such changes in ways that could be correlated with outcomes. To investigate this issue, we conduct an event study analysis to compare pre-trends between counties prior to any change in travel distance. Specifically, we examine the travel distance in period t relative to period $t-1$ to identify any increase of at least 1 mile in travel distance from the previous year. For each county, the first year it experiences such an increase is designated as the treatment year. We then use the Callaway and Sant'Anna (2021) estimator to account for the staggered nature of these changes in travel distance, which necessitates the use of clean control groups (i.e., not-yet-treated or never-treated groups) for conducting event studies under heterogeneous treatment effects.[10]

We present our event study estimates in Figure A3. We find no evidence of a statistically significant pre-trend in child maltreatment, indicating that the counties were not experiencing differing trends in child maltreatment prior to the change in travel distance. Additionally, we observe evidence of an increase in child maltreatment in the post-change period. Indeed, when aggregating the event study coefficients, our static difference-in-differences coefficient is both positive and statistically significant. Note also that this estimation strategy alleviates concerns associated with TWFE, particularly when estimating the average level treatment effects.

4.1. Heterogeneous Effects

Child maltreatment along the age dimension. We explore the changes in child maltreatment as the travel distance to the nearest abortion varies. We expect this relationship to be particularly pronounced for newborn children under one year of age. In Figure 2, we investigate the impact of abortion facility distance on child maltreatment across a range of ages up to 17 years. Specifically, we plot the percentage change in child maltreatment as travel distance increases by 100 miles, alongside the associated 90% and 95% confidence intervals. A clear pattern emerges from this analysis: we observe a positive and statistically significant ($p < 0.05$) increase in child maltreatment exclusively among children younger than one year. This further supports the idea that we are not detecting policy changes in other dimensions or spurious effects that increase maltreatment among older children. The effects are solely concentrated on marginal children who would not have been born in the absence of increased travel distance.

In Appendix Table A3, we present estimates using linear, quadratic, and categorical measures of travel distance for children aged 2-6, 7-12, and 13-17. We also report results from an alternative specification that includes state-by-year fixed effects. Almost all of these estimates are statistically insignificant, and the few significant ones display signs that are theoretically implausible. Notably, for age groups older than one year, we do not observe any statistically significant increases in child maltreatment, independent of the functional form of the travel distance.

Heterogeneous effects by child characteristics. We next explore how the impact of

[10] We take long differences for both pre- and post-periods to estimate the event study coefficients, indicating that the observed changes in child maltreatment in both the pre- and post-periods are measured relative to event period -1.

abortion facility distance on child maltreatment varies by child race and gender. Figure 3 presents our baseline estimate alongside estimates by child race and gender. In terms of race, we observe notable increases in child maltreatment among non-White children as the distance to abortion facilities increases. Specifically, a 100-mile increase in travel distance increases child maltreatment by 22.2% among non-White children ($p < 0.10$). Conversely, we do not observe statistically significant changes in child maltreatment among White children. In terms of gender, both male and female children show an increase in maltreatment as travel distance lengthens, with the increase being more salient for males than females. In particular, females exhibit a 20.2% increase in child maltreatment ($p < 0.10$), while males show a 22.5% increase ($p < 0.05$).

Heterogeneous effects by geographic characteristics. We further investigate how the impact of abortion facility distance on child maltreatment varies by state policy measures and county characteristics. In Figure 3, we present estimates by county-level poverty rate, minority population, and rural population. Additionally, we examine the influence of mandatory waiting laws as a state-level policy measure on the relationship between travel distance and child maltreatment. Our analysis reveals four key findings. First, counties with an above-median poverty rate experience a 33.2% increase in child maltreatment ($p < 0.05$) as the distance to abortion facilities increases. Moreover, counties with above-median minority and rural populations see increases in child maltreatment by 23.4% ($p < 0.05$) and 22% ($p < 0.05$), respectively. Conversely, wealthier counties and those with more urban and fewer minority populations do not experience a statistically significant change in child maltreatment. The impact on minority populations aligns with our findings related to child race. Interestingly, we also observe a 23.1% increase in child maltreatment ($p < 0.05$) in states with mandatory waiting laws for women seeking abortions. This suggests that mandatory waiting laws exacerbate the negative effects of increased travel distance to abortion facilities on child maltreatment rates.

4.2. Alternative Data and Additional Heterogeneity Analyses

As mentioned in our data section, we supplement our analysis with data from NCANDS. Using this data, we explore changes in alleged and substantiated child maltreatment cases as travel distance increases. Additionally, we incorporate an array of caregiver risk factors to examine heterogeneity along different dimensions.

We report our key estimates in Figure 4. For the total number of child maltreatment cases, we find statistically significant positive effects mainly on substantiated cases. However, when we stratify by caregiver risk factors, we observe significant positive effects across the board. In particular, we find a 6% increase ($p < 0.05$) in substantiated cases as the travel distance increases by 100 miles. Additionally, our findings indicate notable heterogeneity in caregiver risk factors, providing a basis for underlying mechanisms that we explore in detail later.

Our findings show a pronounced impact of increased travel distance on both alleged and substantiated child maltreatment cases in families where the caregiver experiences financial problems or receives social assistance. Specifically, alleged and substantiated child maltreatment increases by 23.3% ($p < 0.05$) and 14.9% ($p < 0.10$), respectively, if the caregiver already experiences financial problems. These increases in child maltreatment are also notable when pooling caregivers with financial problems or in need of social assistance. In Figure A4, we further stratify our analysis by child race and find results consistent with our earlier analysis. For both total alleged and substantiated cases, we observe pronounced impacts of increased travel distance on child maltreatment among non-White children, as opposed to White children.

Additionally, the increase in child maltreatment due to increased travel distance may be particularly salient among families where the caregiver has a history of drug abuse, alcohol abuse, mental health problems, or intimate partner violence (IPV). The psychological strain associated with an unwanted birth or child could be exacerbated in families experiencing mental health, addiction, and domestic violence issues. Interestingly, in Figure 5, we do not find strong evidence supporting this hypothesis, particularly when the caregiver risk factor includes drug abuse, alcohol abuse, or mental health problems. One exception is domestic violence. We find a marginally significant increase in substantiated child maltreatment by about 19.9% ($p < 0.10$) when the caregiver has a history of IPV.

We report these estimates from our linear specification, alongside alternative specifications, in Tables A4 and A5. In short, both the quadratic and categorical specifications confirm our earlier findings that there is evidence of nonlinear effects of travel distance on child maltreatment, particularly in substantiated cases. We observe similar nonlinearity when the caregiver experiences financial problems, receives social assistance, or has a history of IPV. Differing from our earlier analysis, there is also some evidence in the categorical case that child maltreatment may increase in families experiencing mental health problems.

Taken together, these findings highlight that financial problems likely make families more vulnerable to increased travel distances to the nearest abortion facility. Consequently, the income effect associated with unwanted births could be an important channel through which increased travel distance impacts child maltreatment.

4.3. Mechanisms

There are multiple pathways that could potentially explain how increased travel distance to the nearest abortion facilities impacts child maltreatment. An important channel relates to economic strain resulting from unwanted births. Specifically, the costs associated with raising a child - including healthcare, education, and daily care - can substantially strain family budgets, especially if the pregnancy was unintended and the family was unprepared. This situation could lead to a resource allocation problem within the family, where distributing resources adequately among all children becomes challenging, potentially resulting in neglect or child maltreatment. We use eviction filings as a measure of economic strain and financial resource scarcity. This mechanism assesses the income effect: an increased financial burden on families due to unplanned children could lead to allocation issues, increasing the risk of eviction if rent or mortgage payments are not made on time.

In Figure 6, we present our baseline estimate, derived from our most comprehensive specification, alongside estimates stratified by county characteristics. We find that a 100-mile increase in the distance to the nearest abortion facility increases the number of eviction filings within a county by 36.1% ($p < 0.05$). We present the Poisson estimates for all our specifications in Appendix Table A6, with our baseline estimate highlighted in column (2). In terms of eviction filings, our analysis does not reveal strong evidence of nonlinear effects, particularly when accounting for state-by-year fixed effects. Nonetheless, the increase in travel distance to abortion facilities has a statistically significant impact on eviction filings.

We further explore the impact of travel distance to abortion facilities on eviction filings, focusing on variations by county characteristics. Our findings align with the heterogeneity analysis previously introduced. Specifically, counties with a higher proportion of the female population aged 18-44 in the third or second tertile experience increases in eviction filings by 36.1% ($p < 0.05$) and 24.3% ($p < 0.05$), respectively, for every 100-mile increase in travel distance. In addition, counties with above-median poverty rates and those with above-median minority or rural populations exhibit pronounced increases in evictions, which correlates with our earlier findings of higher child maltreatment rates in these areas. Conversely, wealthier counties and those with more urban and fewer minority populations do not show a statistically significant change in eviction rates.

5. Conclusion

In this paper, we study the impact of the distance to the nearest abortion clinic on child maltreatment, specifically focusing on children under the age of one. Our findings indicate a significant increase in maltreatment cases associated with increased travel distance to abortion facilities, suggesting that limited access to reproductive health services may lead to higher rates of child victimization. In fact, our back-of-the-envelope calculation suggests that increasing the travel distance to the nearest abortion facility by 100 miles results in an additional cost of $183,808 per child.[11] Therefore, our analysis underscores the importance of accessible reproductive health services and their relation to child welfare.

Our paper sheds several policy insights. First, our findings indicate that challenges leading to maltreatment are more acute during the infant stage of children when the consequences of unintended parenthood are most immediate. This temporal delineation underpins the policy implications of ensuring adequate access to reproductive health services. Policies that support family planning and birth spacing may play a crucial role in preventing child maltreatment, highlighting an essential intersection between reproductive healthcare accessibility and child welfare.

Our stratification analyses highlight the critical need for healthcare policies that address the unique needs and challenges faced by various demographic populations. The racial disparities that we document in the relationship between abortion access and child maltreatment indicate that policies restricting access to abortion services could inadvertently worsen existing societal inequities, leading to greater incidences of child maltreatment among the most vulnerable populations. Therefore, it is essential to consider reproductive healthcare as an integral component of broader social policies aimed at reducing racial disparities.

Our analysis also reveals the important role that economic conditions play in moderating the relationship between proximity to abortion services and child maltreatment. Particularly in economically disadvantaged areas, the lack of access to essential reproductive health services is not just a problem about access to healthcare, but a socioeconomic one as well, with far-reaching implications for child welfare. In such communities, where resources are often scarce and social safety nets may be lacking, the inability to access abortion services can exacerbate existing stressors. The economic strain of an unplanned child can lead to outcomes that ripple through families and communities, potentially increasing the incidence of child maltreatment. Our findings highlight the need for policy interventions that are responsive to the economic realities

[11] Earlier studies estimate the lifetime economic burden of child maltreatment to be $582 billion (Klika, Rosenzweig, and Merrick, 2020). Using this cost estimate, we calculate the base cost per child as $582 billion divided by 682,375. The number in the denominator, 682,375, represents the national estimate of unique victims of child abuse and neglect averaged over the years 2011-2018. Thus, the additional cost per child due to a 100-mile increase in travel distance is calculated as follows:

$$\underbrace{\$847,042}_{Base\ Cost} \times \underbrace{0.217}_{\%\ Increase} = \$183,808.$$

of these areas. Policies must move beyond a one-size-fits-all approach, acknowledging the diverse economic landscapes across different counties.

Interventions could include the provision of comprehensive family support programs that offer economic assistance, education, and childcare resources, which could alleviate some of the pressures that contribute to maltreatment. Furthermore, improving transportation infrastructure or subsidizing travel for medical services could directly address the increased travel distances that correlate with higher maltreatment rates. Policy efforts must also focus on creating sustainable economic growth within these communities to address the root causes of the disparities we observe. This might involve investment in job creation, education, and community development initiatives that can provide long-term stability for families. Incorporating these socioeconomic considerations into the design and implementation of healthcare policies, especially those pertaining to reproductive health, is essential. By doing so, we can work towards a holistic strategy that not only addresses the immediate healthcare needs of individuals but also fosters an environment that supports the overall well-being and development of children.

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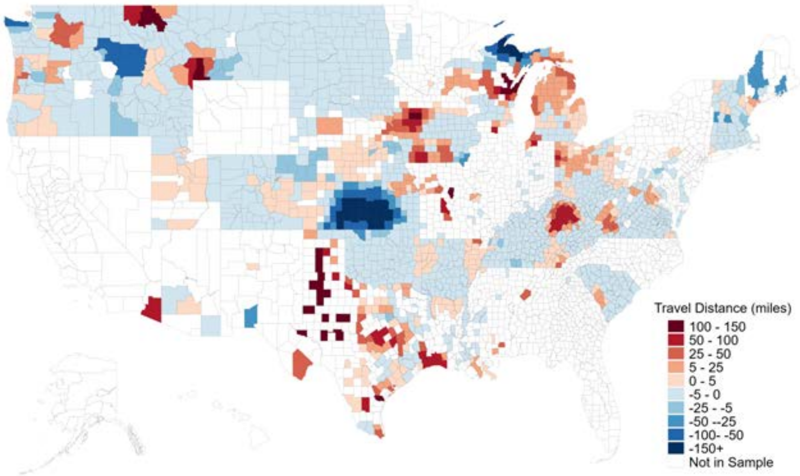
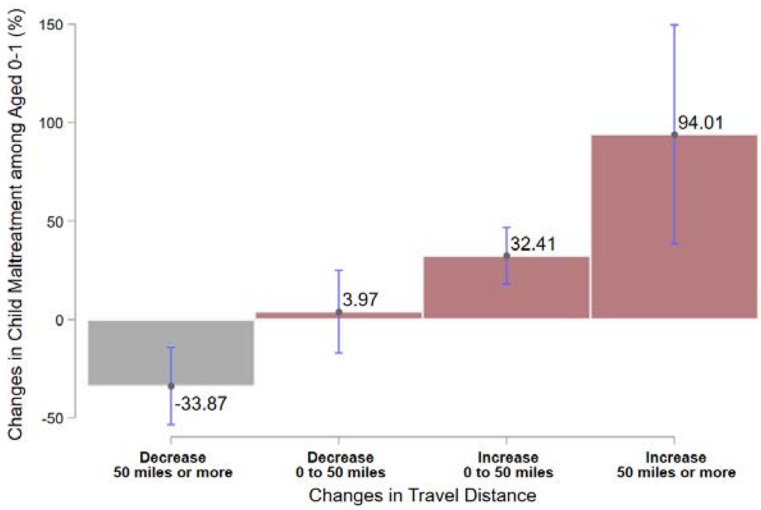


(a) Change in Travel Distance to the Nearest Abortion Facility between 2010 and 2017



(b) Change in Child Maltreatment

Figure 1. Variations in Abortion Facility Distance and Child Maltreatment

Notes: The top panel displays the changes in travel distance to the nearest abortion facility between 2010 and 2017 geographically in our analytical sample. A positive value indicates an increase in travel distance from 2010 to 2017. The bottom panel displays the correlation between change in child maltreatment among children of 1 year old or below against changes in travel distance in our study period. The change in child maltreatment (CM) is calculated as $\frac{CM_{2018}-CM_{2011}}{CM_{2011}} \times 100\%$. The change in travel distance is the difference in travel distance between 2010 and 2017.

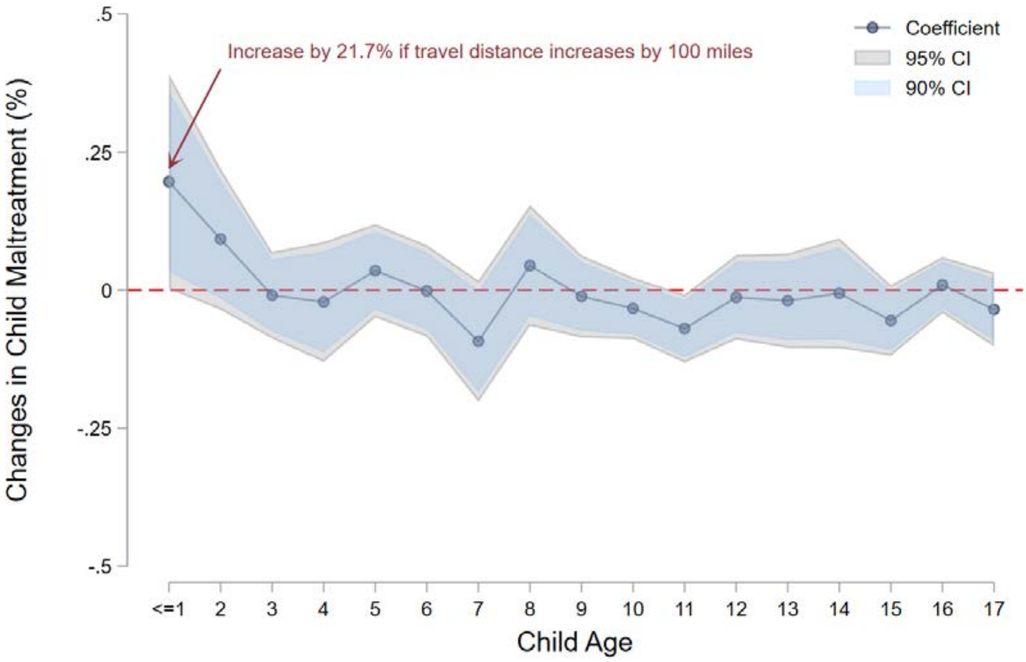


Figure 2. Effects of Abortion Facility Distance on Child Maltreatment by Age

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment by child age, alongside the associated 90% and 95% confidence intervals. Child maltreatment is measured in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis employs a Poisson model similar to column (1) in Table 1. Specifically, we account for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

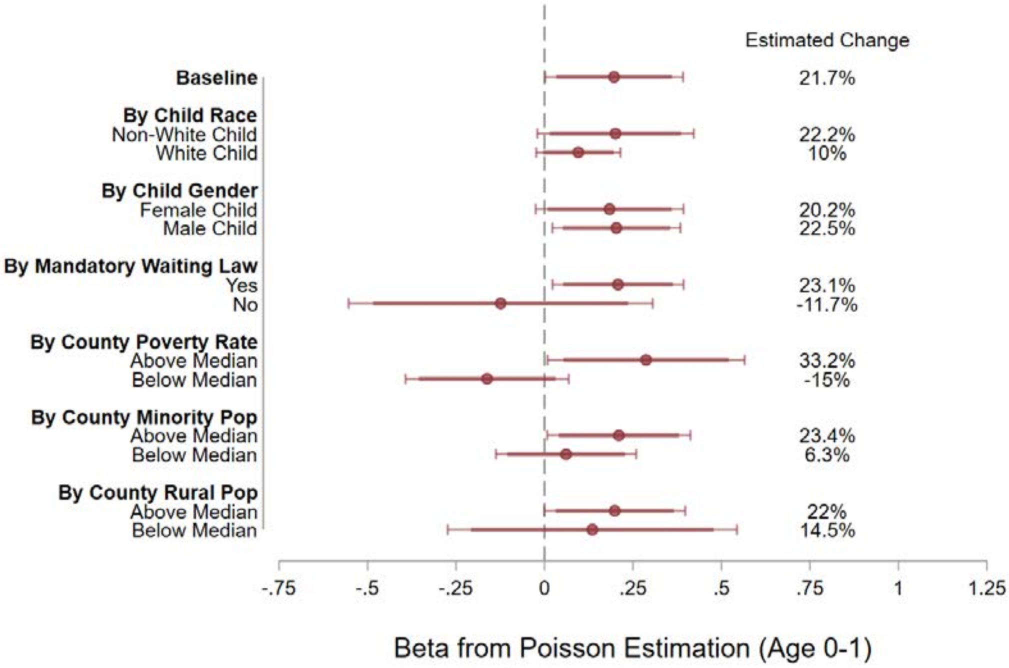


Figure 3. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment, alongside the associated 90% and 95% confidence intervals, by child race, gender, or county characteristics. The primary outcome is the incidence of child maltreatment for children aged one year or younger. Child maltreatment is measured in period $t+1$, while changes in abortion facility distance are measured in period t. The analysis employs a Poisson model similar to column (1) in Table 1. Specifically, we account for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta})-1)\times 100\%$.

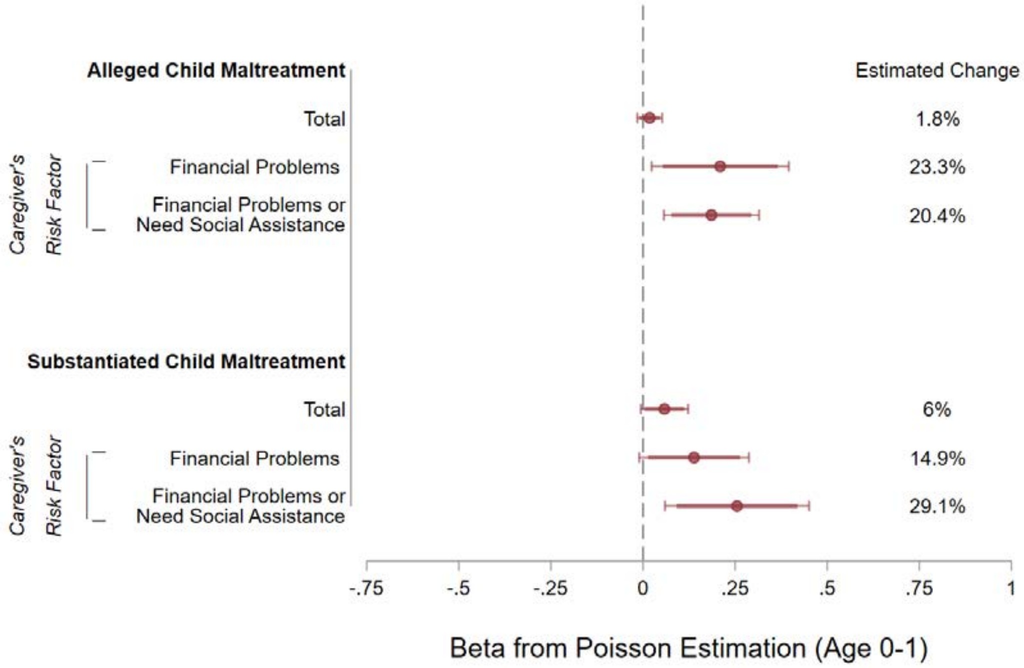


Figure 4. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: NCANDS

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the number of child maltreatment cases, alongside the associated 90% and 95% confidence intervals. The analysis uses alternative child maltreatment data from the National Child Abuse and Neglect Data System (NCANDS), distinguishing between the number of alleged and substantiated cases. We further conduct additional analysis exploring changes in child maltreatment by the caregiver's risk factors. The primary outcome is the incidence of child maltreatment for children aged one year or younger. Child maltreatment is measured in period $t+1$, while changes in abortion facility distance are measured in period t. The analysis employs a Poisson model similar to column (1) in Table 1. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

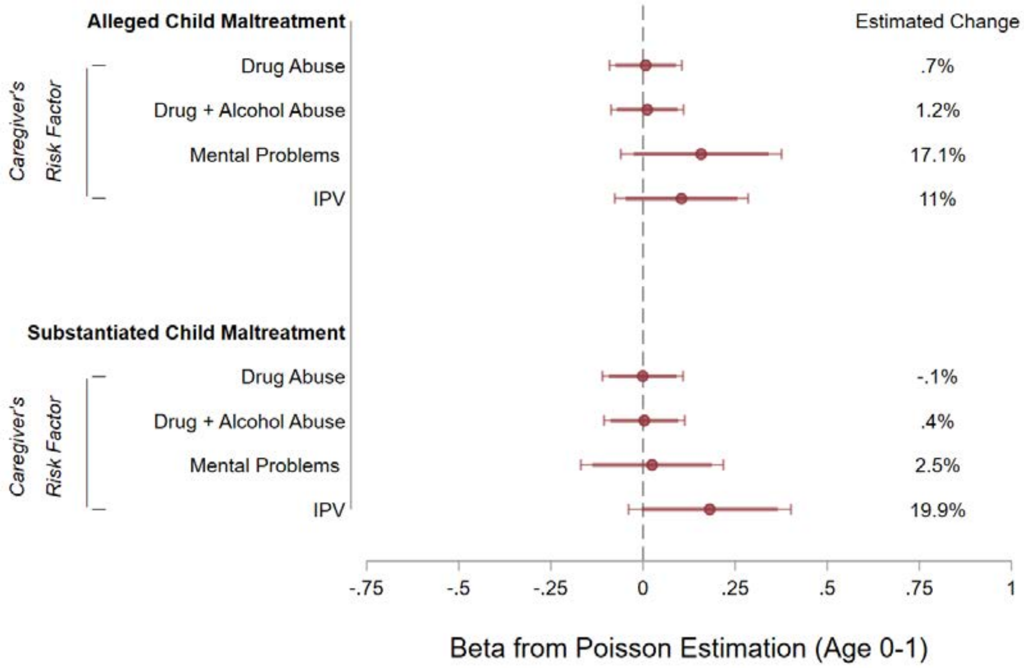


Figure 5. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Additional Caregiver Risk Factors, NCANDS

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment, alongside the associated 90% and 95% confidence intervals. The analysis uses alternative child maltreatment data from the National Child Abuse and Neglect Data System (NCANDS), distinguishing between the number of alleged and substantiated cases. We further conduct additional analysis exploring changes in child maltreatment by the caregiver's additional risk factors. The primary outcome is the incidence of child maltreatment for children aged one year or younger. Child maltreatment is measured in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis employs a Poisson model similar to column (1) in Table 1. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

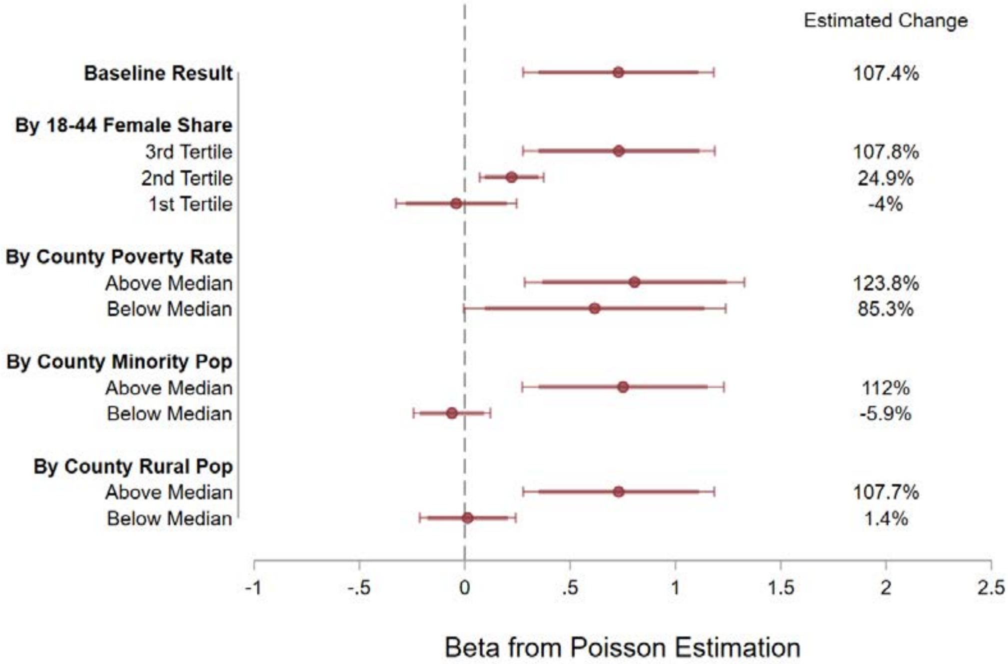


Figure 6. Heterogeneous Effects of Abortion Facility Distance on Evictions

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of eviction filings stratified by county characteristics, alongside the associated 90% and 95% confidence intervals. The primary outcome is the number of eviction filings. Eviction filings are measured in period $t + 1$, while changes in abortion facility distance are measured in period t. We use a Poisson regression model with an exposure of the number of households renting a property in each county. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

Table 1. Impact of Abortion Facility Distance on Child Maltreatment

	Child Maltreatment (Children Aged 0-1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (100 miles)	0.196**	0.189**	0.507***	0.367**		
	(0.099)	(0.080)	(0.179)	(0.182)		
Distance (100 miles) Squared			-0.074**	-0.036		
			(0.029)	(0.031)		
Distance: 50-100 miles					0.307*	0.339**
					(0.182)	(0.140)
Distance: 100-150 miles					0.252	0.372*
					(0.246)	(0.215)
Distance: 150-200 miles					0.800***	0.730***
					(0.277)	(0.208)
Distance: 200+ miles					0.115	0.658*
					(0.356)	(0.390)
N	38,827	38,827	38,827	38,827	38,827	38,827
Clusters	1,708	1,708	1,708	1,708	1,708	1,708
Dep. Var. Mean	16.907	16.907	16.907	16.907	16.907	16.907
County FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
County Demographics	√	√	√	√	√	√
State Policy Measures	√		√		√	
State × Year FE		√		√		√

Notes: This table presents the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment for children aged one year old or younger. Child maltreatment is measured in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis explores nonlinear effects of abortion distance in separate columns and includes specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix for Online Publication

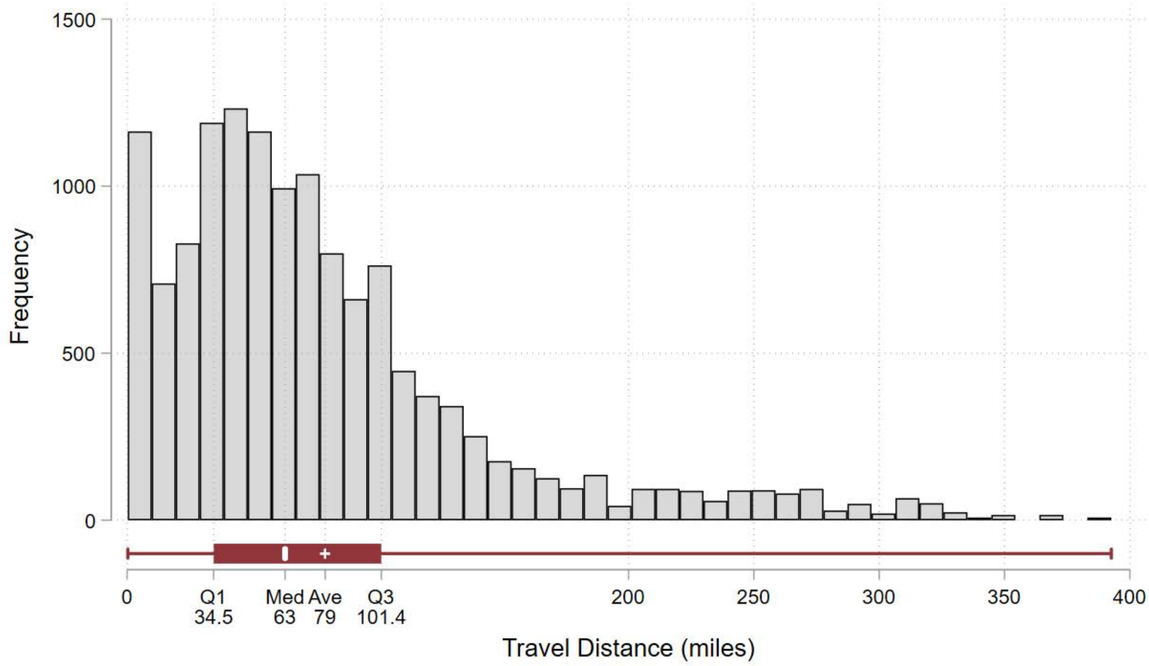


Figure A1. Histogram of Abortion Facility Distance

Notes: This figure displays the distribution of travel distance to the nearest abortion facility based on the analytical county-year sample from 2010 to 2017.

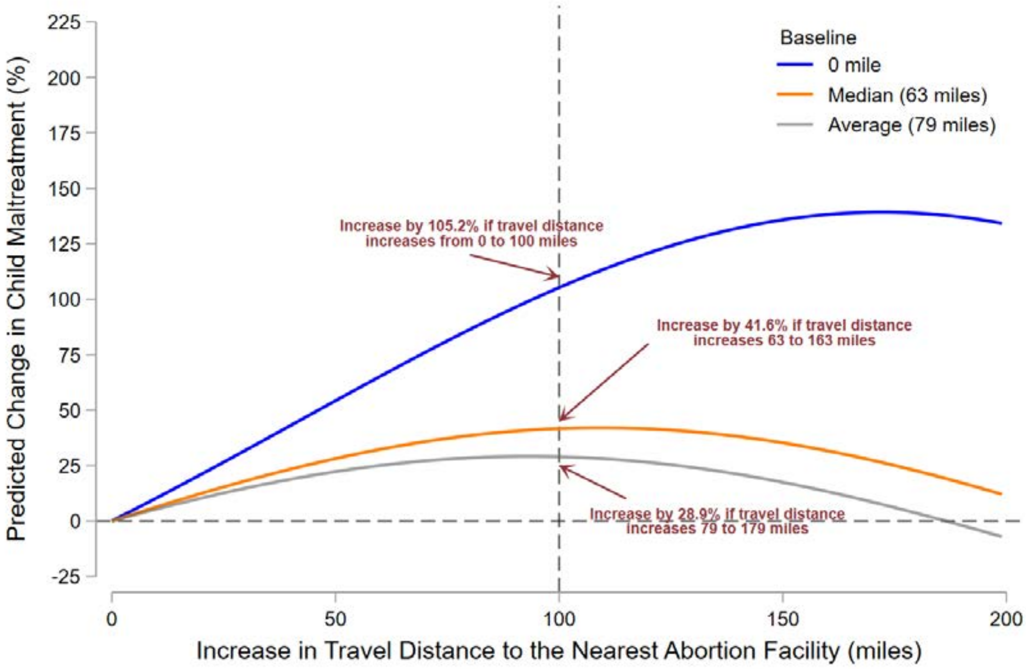


Figure A2. Nonlinear Effects of Abortion Facility Distance on Child Maltreatment

Notes: This figure displays the nonlinear effect of travel distance to the nearest abortion facility on the incidence of child maltreatment for children aged one year or younger. Each curve shows the nonlinear effect given a baseline distance. Each curve is based on a Poisson estimation as specified in column (3) in Table 1. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

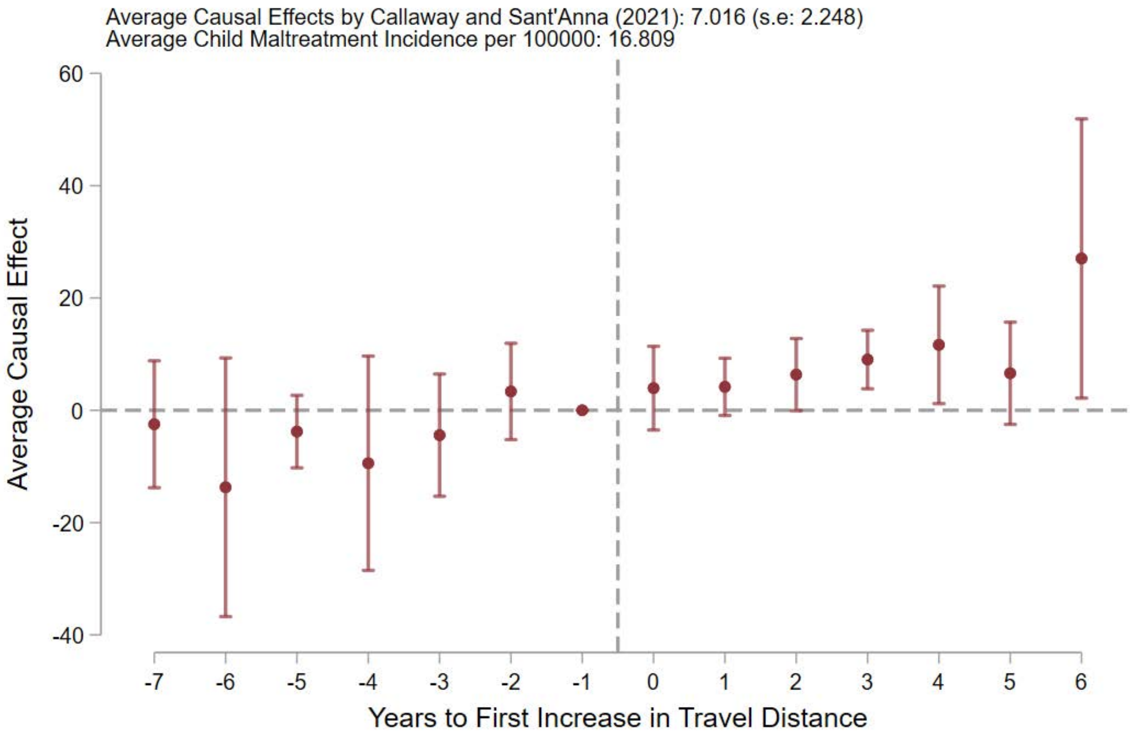


Figure A3. Effects of Abortion Facility Distance on Child Maltreatment: Event Study

Notes: This figure shows the event study analysis to compare pre-trends between counties before any change in travel distance, using the Callaway and Sant'Anna (2021) estimator. The primary outcome is the incidence of child maltreatment for children aged one year or younger per 100,000 child population. We estimate a linear regression weighted by the population covered by each agency. We examine the travel distance in period t relative to period $t-1$ to identify any increase of at least 1 mile in travel distance from the previous year. For each county, the first year it experiences such an increase is designated as the treatment year. We then use the Callaway and Sant'Anna (2021) estimator to account for the staggered nature of these changes in travel distance. We take long differences for both pre- and post-periods to estimate the event study coefficients, indicating that the observed changes in child maltreatment in both the pre- and post-periods are measured relative to event period -1. The 95% confidence intervals are reported.

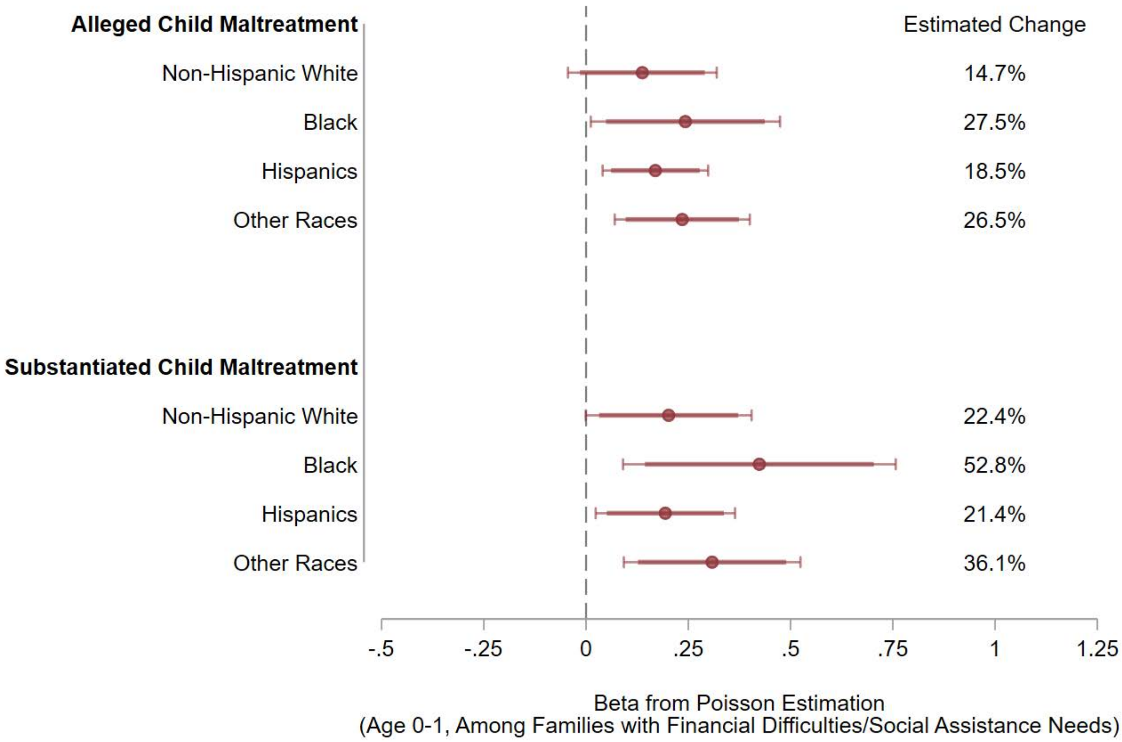


Figure A4. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Racial Characteristics, NCANDS

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment by racial characteristics, alongside the associated 90% and 95% confidence intervals. We restrict our analysis to families experiencing financial problems or needing social assistance. The analysis uses alternative child maltreatment data from the National Child Abuse and Neglect Data System (NCANDS), distinguishing between the number of alleged and substantiated cases. The primary outcome is the incidence of child maltreatment for children aged one year old or younger. Child maltreatment is measured in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis employs a Poisson model similar to column (1) in Table 1. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). The state-level policy measures include mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

Table A1. Number of agencies, counties, and states in analytical sample

Year (1)	Agencies (2)	Counties (3)	States (4)
2011	4,405	1,431	35
2012	4,660	1,478	35
2013	4,705	1,482	36
2014	4,739	1,485	36
2015	4,834	1,497	36
2016	5,076	1,525	37
2017	5,149	1,561	40
2018	5,259	1,626	41
Unique Obs.	6,104	1,708	41

Table A2. Impact of the Abortion Rate on Any Increase in Abortion Facility Distance

	Indicator for Travel Distance Increases $(t+1)$ by ...							
	1 mile		10 miles		25 miles		50 miles	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abortion Rate (t)	0.00059	-0.00298*	0.00136	-0.00069	0.00116	-0.00024	0.00030	-0.00074
	(0.00178)	(0.00178)	(0.00112)	(0.00106)	(0.00094)	(0.00097)	(0.00054)	(0.00066)
N	16,405	16,405	16,405	16,405	16,405	16,405	16,405	16,405
Clusters	2,139	2,139	2,139	2,139	2,139	2,139	2,139	2,139
Dep. Var. Mean	0.086	0.086	0.038	0.038	0.020	0.020	0.010	0.010
County FE	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
County Demographics	√	√	√	√	√	√	√	√
State Policy Measures	√		√		√		√	
State × Year FE		√		√		√		√

Notes: This table presents the findings on the impact of the abortion rate on the travel distance to the nearest abortion facility. Travel distance is measured in period $t+1$, while changes in the abortion rate are measured in period t. The analysis includes separate specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. Impact of Abortion Facility Distance on Child Maltreatment by Age – Placebo Test

	Child Maltreatment Among Children Aged ...					
	2-6		7-12		13-17	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Linear						
Distance (100 miles)	0.016	0.022	-0.029	-0.057**	-0.021	-0.019
	(0.042)	(0.035)	(0.031)	(0.025)	(0.026)	(0.025)
Panel B: Quadratic						
Distance (100 miles)	0.116	-0.033	0.026	-0.122*	0.001	-0.065
	(0.091)	(0.091)	(0.072)	(0.068)	(0.078)	(0.072)
Distance (100 miles) Squared	-0.024	0.011	-0.013	0.013	-0.005	0.009
	(0.017)	(0.013)	(0.012)	(0.011)	(0.013)	(0.011)
Panel C: Categorical						
Distance: 50-100 miles	0.059	0.020	0.002	-0.084	0.022	-0.063
	(0.114)	(0.070)	(0.062)	(0.055)	(0.057)	(0.041)
Distance: 100-150 miles	0.018	-0.062	-0.032	0.005	0.016	-0.045
	(0.136)	(0.132)	(0.095)	(0.106)	(0.103)	(0.078)
Distance: 150-200 miles	0.142	0.122	-0.019	-0.026	-0.065	-0.043
	(0.111)	(0.130)	(0.094)	(0.107)	(0.104)	(0.094)
Distance: 200+ miles	-0.208	0.111	-0.303***	-0.146	-0.083	-0.047
	(0.172)	(0.136)	(0.115)	(0.127)	(0.117)	(0.116)
N	38,827	38,827	38,827	38,827	38,827	38,827
Clusters	1,708	1,708	1,708	1,708	1,708	1,708
Dep. Var. Mean	55.064	55.064	57.032	57.032	75.213	75.213
County FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
County Demographics	√	√	√	√	√	√
State Policy Measures	√		√		√	
State × Year FE		√		√		√

Notes: This table presents the findings on the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment. Child maltreatment is measured in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis explores nonlinear effects of abortion distance in separate columns and includes specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Impact of Abortion Distance on Child Maltreatment: Alleged Child Maltreatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Fin. Prob	Fin. Prob Social Assistance	Drug Abuse	Drug Abuse Alcohol Abuse	Mental Prob	IPV
Panel A: Linear							
Distance (100 miles)	0.018	0.209**	0.186***	0.007	0.012	0.158	0.104
	(0.017)	(0.095)	(0.066)	(0.050)	(0.050)	(0.111)	(0.092)
Panel B: Quadratic							
Distance (100 miles)	0.037	0.345**	0.338***	0.101	0.096	0.260	0.499**
	(0.031)	(0.140)	(0.120)	(0.092)	(0.091)	(0.225)	(0.206)
Distance (100 miles) Squared	-0.005	-0.035	-0.040**	-0.022	-0.020	-0.024	-0.088**
	(0.005)	(0.022)	(0.019)	(0.014)	(0.013)	(0.035)	(0.036)
Panel C: Categorical							
Distance: 50-100 miles	0.046	0.345*	0.426***	0.062	0.061	0.777***	0.225
	(0.031)	(0.189)	(0.161)	(0.134)	(0.135)	(0.237)	(0.156)
Distance: 100-150 miles	0.078	0.501*	0.310**	0.139	0.131	0.623**	0.091
	(0.050)	(0.278)	(0.142)	(0.137)	(0.134)	(0.309)	(0.210)
Distance: 150-200 miles	0.043	0.439	0.781**	-0.010	0.021	1.515***	0.457
	(0.056)	(0.443)	(0.367)	(0.243)	(0.254)	(0.482)	(0.323)
Distance: 200+ miles	0.061	0.820*	0.755**	-0.152	-0.101	0.905	-0.207
	(0.087)	(0.429)	(0.317)	(0.271)	(0.277)	(0.645)	(0.404)
N	5981	5981	5981	5981	5981	5981	5981
Clusters	965	965	965	965	965	965	965
Child Maltreatment Mean	981.701	68.071	182.994	128.931	137.530	35.703	91.498
County Demographic	√	√	√	√	√	√	√
County FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√

Notes: This table presents the findings on the impact of travel distance to the nearest abortion facility on the number of alleged child maltreatment among children aged one year old or younger in each county and year based on NCANDS data. Child maltreatment cases are in period $t+1$, while changes in abortion facility distance are measured in period t. The analysis explores nonlinear effects of abortion distance in separate columns and includes specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Impact of Abortion Distance on Child Maltreatment: Substantiated Child Maltreatment

	(1) Total	(2) Fin. Prob	(3) Fin. Prob Social Assistance	(4) Drug Abuse	(5) Drug Abuse Alcohol Abuse	(6) Mental Prob	(7) IPV
Panel A: Linear							
Distance (100 miles)	0.058*	0.138*	0.255**	-0.001	0.004	0.025	0.181
	(0.033)	(0.076)	(0.100)	(0.056)	(0.056)	(0.099)	(0.112)
Panel B: Quadratic							
Distance (100 miles)	0.170**	0.230**	0.521***	0.161	0.156	0.106	0.688***
	(0.067)	(0.115)	(0.173)	(0.098)	(0.096)	(0.205)	(0.266)
	-0.026**	-0.021	-0.064***	-0.037***	-0.035**	-0.018	-0.109**
Distance (100 miles) Squared	(0.011)	(0.019)	(0.023)	(0.014)	(0.014)	(0.031)	(0.043)
Panel C: Categorical							
Distance: 50-100 miles	0.193***	0.238	0.547**	0.134	0.132	0.481**	0.569***
	(0.067)	(0.177)	(0.228)	(0.132)	(0.132)	(0.191)	(0.179)
Distance: 100-150 miles	0.100	0.375	0.512**	0.103	0.094	0.283	0.311
	(0.104)	(0.257)	(0.219)	(0.181)	(0.179)	(0.274)	(0.233)
Distance: 150-200 miles	0.084	0.059	0.993*	-0.017	0.011	0.598	0.835**
	(0.159)	(0.410)	(0.530)	(0.264)	(0.276)	(0.502)	(0.372)
Distance: 200+ miles	0.206	0.652*	0.941**	-0.224	-0.174	0.204	0.306
	(0.142)	(0.380)	(0.451)	(0.272)	(0.282)	(0.540)	(0.461)
N	5981	5981	5981	5981	5981	5981	5981
Clusters	965	965	965	965	965	965	965
Child Maltreatment Mean	254.597	23.647	57.047	66.260	70.186	12.417	45.424
County Demographic	√	√	√	√	√	√	√
County FE	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√

Notes: This table presents the findings on the impact of travel distance to the nearest abortion facility on the number of alleged child maltreatment among children aged one year old or younger in each county and year based on NCANDS data. Child maltreatment cases are in period $t + 1$, while changes in abortion facility distance are measured in period t. The analysis explores nonlinear effects of abortion distance in separate columns and includes specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Impact of Abortion Facility Distance on Eviction Filings

	Eviction Filings					
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (100 miles)	0.729***	0.308***	1.161**	0.306		
	(0.231)	(0.112)	(0.451)	(0.253)		
Distance (100 miles) Squared			-0.236*	0.001		
			(0.142)	(0.083)		
Distance: 50-100 miles					0.518***	0.081
					(0.200)	(0.107)
Distance: 100-150 miles					0.602***	0.064
					(0.225)	(0.195)
Distance: 150-200 miles					0.881***	0.343*
					(293)	(0.189)
Distance: 200+ miles					1.637***	0.926***
					(0.469)	(0.234)
N	19,566	19,566	19,566	19,566	19,566	19,566
Clusters	2,837	2,837	2,837	2,837	2,837	2,837
Dep. Var. Mean	893.388	893.388	893.388	893.388	893.388	893.388
County FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
County Demographics	√	√	√	√	√	√
State Policy Measures	√		√		√	
State × Year FE		√		√		√

Notes: This table presents the findings on the impact of travel distance to the nearest abortion facility on the number of eviction filings. Eviction filings are measured in period $t + 1$, while changes in abortion facility distance are measured in period t. We use a Poisson regression model with an exposure of the number of households renting a property in each county. The analysis explores nonlinear effects of abortion distance in separate columns and includes specifications that control for state-by-year fixed effects. Across all specifications, we account for county fixed effects, year fixed effects, and county demographics. These demographics include the share of white females aged 15-44, the percentage of children under 17, median household income (log-transformed), the unemployment rate, the number of psychiatric treatment centers, a categorical variable for the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). Additionally, we adjust for state policy measures, such as mandatory abortion waiting periods, parental involvement laws, minimum wage, and EITC refund statuses. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.