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ABORTION ACCESS AND CHILD MALTREATMENT

Erkmen G. Aslim

Wei Fu

Erdal Tekin

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1050 Massachusetts Avenue

Cambridge, MA 02138

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ABSTRACT

This study examines the link between abortion access and child maltreatment using data from the National Incident-Based Reporting System, National Child Abuse and Neglect Data System (NCANDS), and the Myers abortion facility database from 2011 to 2018. A 100-mile increase in travel distance to the nearest abortion facility increases maltreatment reports by 8.5%, driven by child neglect and physical abuse, with strongest effects for infants, non-White children, and those in disadvantaged, minority, and rural areas. Analyses with NCANDS data and eviction records highlight economic stability and housing security as mediators. These findings highlight the importance of reproductive healthcare access in reducing maltreatment and alleviating associated socioeconomic challenges.

Erkmen G. Aslim
University of Vermont
easlim@uvm.edu

Wei Fu
University of Louisville
wei.fu@louisville.edu

Erdal Tekin
American University
School of Public Affairs
and IZA
and also NBER
tekin@american.edu

1. Introduction

Child maltreatment, which includes neglect, physical, emotional and sexual abuse, is a serious and prevalent societal problem in the United States. In 2023, 546,159 child victims were reported at a rate of 7.4 per 1,000 children with an estimated 2,000 fatalities ([USDHHS, 2025](#)). The youngest children are particularly vulnerable, with those under the age one accounting 44.0 percent of child fatalities with a fatality rate of 24.11 per 100,000 children in that age range in 2023 ([USDHHS, 2025](#)). The economic toll is staggering, with the lifetime cost of child maltreatment reaching \$592 billion in 2018, comparable to major diseases like heart disease and diabetes ([Klika, Rosenzweig, and Merrick, 2020](#); [CDC, 2022](#)). Beyond immediate harm, child maltreatment has long-term effects on psychological, behavioral, and physical health ([Lansford et al., 2002](#); [Fletcher, 2009](#); [Herringa et al., 2013](#); [Min et al., 2013](#); [Danese and Widom, 2023](#)) as well as lifelong repercussions, such as reduced employment and earnings ([Currie and Spatz Widom, 2010](#)), lower education levels ([Currie and Spatz Widom, 2010](#); [Henkhaus, 2022](#)), higher incarceration and crime ([Currie and Tekin, 2012](#)), and increased likelihood of teen pregnancy ([Anda et al., 2001](#)). Moreover, maltreatment is more common among lower socioeconomic families, exacerbating disparities in the life chances of children from different backgrounds ([Paxson and Waldfogel, 1999, 2002](#)). Therefore, understanding and addressing the factors and conditions contributing to child maltreatment is critically important.

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 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

¹Using 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 anxiety, lower self-esteem, and reduced life satisfaction. [Miller, Wherry, and Foster \(2023\)](#) further find that denied abortions lead to significant increases in financial distress.

suggests a basis for hypothesizing that children born to mothers facing a higher barrier to abortion access may encounter poorer outcomes compared to those born to mothers facing lower barriers.

The link between abortion access and child maltreatment has gained importance following recent shifts in U.S. abortion policies, with more restrictive laws in several states potentially increasing unwanted or unplanned births. This issue is further heightened by the U.S. Supreme Court’s 2022 decision to overturn *Roe v. Wade*, ending decades of federally protected abortion rights. This ruling could prompt additional policies that exacerbate barriers to abortion services, potentially leading to more vulnerable children at risk of maltreatment.

There is limited research exploring the effects of abortion access on child welfare outcomes. Using state-level data, [Bitler and Zavodny \(2002, 2004\)](#) found that abortion legalization and less restrictive access, including Medicaid funding and parental involvement laws, reduced child maltreatment. [Adkins et al. \(2024\)](#) linked Targeted Regulation of Abortion Providers (TRAP) laws—such as building, transfer agreement, and admitting privilege requirements—to increased foster care placements in states with these restrictions. Similarly, [Sen \(2007\)](#) reported that abortion restrictions, like parental consent laws and funding limitations, were associated with higher rates of fatal child injuries, especially among white children.

Our study extends the existing literature by focusing on the proximity to the nearest abortion facility as a metric for assessing barriers to abortion. We linked child maltreatment incidents from the National Incident-Based Reporting System (NIBRS, 2011–2018) to a novel database on travel distances to abortion facilities constructed by [Myers \(2024\)](#). This metric offers distinct advantages over legal measures, capturing real-world barriers like geographic and transportation challenges that vary within the same legal context. Additionally, travel distance is closely linked to socioeconomic factors, offering insights into how barriers to abortion access affect different population segments. Travel distance is also a measure directly influenced by temporal changes, such as clinic closures or openings, providing a dynamic and generalizable perspective on access over time. Importantly, focusing on travel distance can yield direct policy implications, highlighting specific areas where interventions can improve access to abortion services. Furthermore, our primary analysis at the county level, whereas previous studies have exclusively focused on state-level measures. Lastly, our study focuses on 2011–2018, a period marked by significant challenges to abortion facilities, leading to numerous closures and increased travel distances for many women in the U.S. In contrast, earlier studies used older data, such as [Sen \(2007\)](#) (1981–2002) and [Bitler and Zavodny \(2002, 2004\)](#) (1976–1996).

A key strength of our analysis is the use of multiple datasets. Alongside NIBRS, we utilize NCANDS Child Files (2011–2018), which provide case-specific details on alleged

and substantiated child maltreatment, including child and perpetrator demographics, maltreatment type, and caregiver risk factors such as domestic violence, inadequate housing, financial instability, public assistance reliance, and substance abuse.

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 99 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 analysis reveals a significant positive relationship between increased barriers to reproductive health services and child maltreatment rates, particularly among infants aged 1 year or younger, with an 8.5% rise in maltreatment reports for every 100-mile increase in travel distance to the nearest abortion facility. This finding supports the idea that infants under one year of age are particularly vulnerable and are the most immediate casualties of abortion clinic closures, as their births result directly from pregnancies carried to term due to diminished access to abortion services. It is plausible that the birth of an unplanned child could create spillover effects on older children in the household, as financial and emotional resources are shared within families and may become strained. Although we observe positive associations for older children in general, these effects are not statistically significant. This suggests that, while spillovers are theoretically plausible, the increase in maltreatment is primarily driven by the newborn child, reinforcing our hypothesis that the impact mainly stems from marginal children who would not have been born absent the increased travel distance.

Furthermore, we show that the rise in maltreatment is primarily driven by neglect and physical abuse. Notably, the effects are disproportionately severe for non-White infants, reflecting systemic inequities such as economic disenfranchisement and unequal access to healthcare and social services. These disparities amplify stressors in communities with fewer resources to address the challenges of early parenthood. We also find increased eviction filings in counties with higher childbearing female populations, elevated poverty rates, and rural demographics, underscoring the broader socioeconomic consequences of restricted abortion access.

2. Data

2.1. Child Maltreatment

We use child maltreatment data from the National Incident-Based Reporting System (NIBRS), the national standard for U.S. law enforcement crime data reporting. NIBRS

provides detailed information on crime incidents, including offenses (e.g., assault, murder, intimidation) and victim, offender, and arrestee demographics. However, non-mandatory participation results in inconsistent reporting across agencies. To address this, we follow existing studies (e.g., [Bondurant, Lindo, and Swensen, 2018](#)) and limit our analysis to agencies reporting consistently throughout the year, resulting in an unbalanced agency-year panel, as shown in Table A1. We use [Kaplan \(2021\)](#)’s concatenated NIBRS data for years between 2011 and 2018. Our final sample includes child maltreatment data from 6,021 police agencies across 1,691 counties in 41 states, offering a granular view of maltreatment incidents at the agency level.

Following [Block and Kaplan \(2022\)](#), we examine victim-offender relationships and injury reports to identify child maltreatment cases, focusing on victims under 18. We further restrict offenders to biological parents, stepparents, or the significant others of biological parents to refine our criteria. 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 to test for potential intra-household spillovers. After defining the relevant age group and relationship categories, approximately 75% of offenses against children aged one year or younger involve simple or aggravated assault, categorized as physical abuse.

We supplement our analysis with data from the National Child Abuse and Neglect Data System (NCANDS) Child Files for the years 2011 through 2018.² 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 into county-level child maltreatment measures, following [Evans, Harris, and Kessler \(2022\)](#). Using the most recent fiscal year data for cases appearing in multiple Child Files, as recommended by the NCANDS User’s Guides, we identify the calendar year of the initial maltreatment report to CPS, distinct from the fiscal year of case resolution.³ Only counties consistently present in all Child Files during the sample period are included.

Importantly, NCANDS data enable us to capture not only physical abuse cases, which account for more than 17.9% of the alleged cases and 4% of the substantiated cases, but also child neglect, which comprises more than 76.4% of alleged cases and 85.1% of the substantiated cases. Additionally, we are able to distinguish between alleged and substantiated child maltreatment cases and observe changes in child maltreatment by

²Although 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.

³[Evans, Harris, and Kessler \(2022\)](#) note that 98% of cases are resolved within two years; in our sample, 99.86% of cases are unique.

caregiver risk factors. We are particularly interested in whether the effects of increased travel distance are more pronounced among families in which the caregiver faces financial difficulties or inadequate housing at baseline.⁴

As discussed above, we use two data sources to examine changes in child maltreatment: NIBRS and NCANDS, each with distinct strengths. While NIBRS offers broader geographic coverage, NCANDS captures a wider range of incidents, including those not involving law enforcement. Beyond coverage, the two datasets differ in the severity and administrative pathways of the cases they reflect—NIBRS focuses on legally actionable offenses, whereas NCANDS includes both substantiated and unsubstantiated reports from child protective services. Taken together, they offer a potential bounding exercise: NCANDS may approximate an upper bound on reported maltreatment, while NIBRS reflects a lower bound concentrated on more serious, criminally reported 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 developed through an extensive compilation of information from state licensing databases, current and historical facility websites, Planned Parenthood 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 align with the child maltreatment data, we use the Myers dataset for 2010–2017.⁶ We then aggregate the travel distance data into a county-by-year format to provide an annualized average travel distance for each county and merge it with the preceding year with NIBRS and NCANDS datasets using the county identifiers.

2.3. Eviction Case Filings

We use eviction case filing data from the Eviction Lab at Princeton University ([Gromis et al., 2022](#)), which compiles over 99 million records from 48 states and D.C., including

⁴In NCANDS, inadequate housing is recorded as a caregiver risk factor and generally refers to unstable, unsafe, or substandard living conditions as assessed by CPS during an investigation.

⁵In 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.

⁶Travel distance from period t is linked to child maltreatment from period $t + 1$, abortion access likely impacts births and subsequent child maltreatment in the next period.

73.2 million from LexisNexis Risk Solutions. These records document the eviction process, from lawsuit filings to outcomes, and are aggregated to the case level using probabilistic matching of tenant names and addresses, excluding commercial properties. Our study uses data from 2011 to 2018, including the number of eviction filings and the total number of renting households per county. These data will help us explore the potential financial strain caused by unplanned or unwanted births, which may result from increased travel distances to the nearest abortion facility.⁷

2.4. Descriptive Evidence

Our final analytical sample consists of 38,151 agency-year observations. The average child maltreatment among children under or equal to 1 year old is 16.95 per 100,000 children, with a standard deviation of 83.62. 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 78.3 miles, with a median of 62.7 miles. The distribution is right-skewed, with the longest travel distance approaching 400 miles.

Figure A2 illustrates the variation in travel distances to the nearest abortion facility across counties in our analytical sample from 2010 to 2017. Several counties, particularly in states like North Dakota (ND), South Dakota (SD), Montana (MT), Idaho (ID), Oklahoma (OK), and Maine (ME), saw reduced travel distances, with the largest decrease in Kansas (KS), where distances dropped by over 100 miles following the 2013 reopening of Trust Women after a four-year closure. Reductions in Colorado (CO) and Maine (ME) were driven by increased advanced practice clinicians and expanded telemedicine abortion services, respectively. Conversely, states like Texas (TX), Wisconsin (WI), Michigan (MI), and Ohio (OH) experienced increased travel distances due to supply-side constraints, such as legislative restrictions and increased regulatory and financial pressures on providers, which resulted in clinic closures and operational challenges.

The top panel of Figure 1 displays the relationship between changes in travel distance—capturing both increases and decreases at different levels—and the abortion rate. This serves as a critical first stage in understanding how travel distance influences child maltreatment. Establishing a negative relationship between travel distance to abortion clinics and abortion rates is essential for demonstrating its downstream effect on child maltreatment. Our analysis reveals a strong inverse association: when travel distance to the nearest abortion facility decreases by 50 miles or more, the abortion rate increases by 36.22%, whereas an increase of 50 miles or more leads to a 30.94% decline in the abortion rate. Furthermore, this descriptive analysis indicates a nonlinear

⁷We supplement our analytical data with various county and state characteristics. These data are described in Online Appendix.

relationship between travel distance and the abortion rate.

The bottom panel of Figure 1 displays the correlation between changes in child maltreatment among children aged one year or younger and changes in travel distance over our study period. This figure provides several key insights: notably, an increase in travel distance is associated with a rise in child maltreatment cases. Specifically, counties where travel distance increased by less than 50 miles saw a 32.71% rise in child maltreatment, while those experiencing an increase of 50 miles or more observed a 94.01% surge. Moreover, the figure suggests a monotonic relationship between travel distance and child maltreatment, indicating that as access to abortion services becomes more difficult, the incidence of child maltreatment not only rises 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:

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

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 detailed in the [Other Covariates](#) section of our Online Appendix. Our regression model further includes agency fixed effects, γ_a , 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.

In a continuous treatment setting, the identifying assumptions depend on the causal parameter of interest. We are initially 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:

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

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 . To account for such heterogeneity, we control for travel distance by including categorical indicators for distance ranges in our specifications. This approach offers greater flexibility

in capturing non-linear effects than imposing standard functional forms, such as quadratic or cubic terms.

4. Results

We explore the changes in child maltreatment as the travel distance to the nearest abortion varies. We expect this relationship to be particularly strong 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 95% confidence intervals. A clear pattern emerges from this analysis: we observe a positive and statistically significant increase in child maltreatment exclusively among younger children, particularly those aged 1 or below. 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 8.5% ($p < 0.05$), which serves as our benchmark finding.

We find slight increases in maltreatment for children above the age of one, suggesting potential intrahousehold spillovers; however, these relationships are largely statistically insignificant. Importantly, we do not observe systematic increases in maltreatment across other age groups, supporting the notion that our main results are not driven by unrelated policy changes or spurious factors affecting older children. While there is a modest uptick in maltreatment at age five, possibly reflecting broader effects of limited abortion access and subsequent childbirth within families, there is no consistent pattern in adjacent or older age groups. In short, we find little evidence of substantial spillovers, with effects concentrated predominantly among marginal children who would not have been born without the increase in travel distance.

Our analysis employs a flexible approach to modeling travel distance, exploring both linear and nonlinear effects. Leveraging within-state variation and controlling for state-by-year fixed effects, Table A2 presents the results. Columns (1) and (2) include a quadratic term, suggesting a hump-shaped relationship between travel distance and child maltreatment, though the squared term is statistically insignificant. In columns (3) and (4), we relax functional form assumptions by using categorical distance ranges (30–60, 60–120, 120–240, and 240+ miles), determined through a data-driven approach.⁸ In columns (3) and (4), we find notable increases in maltreatment at distances of 60–120 miles and 120–240 miles, with the latter specification controlling for state-by-year fixed effects. Across specifications, we do not find significant increases in maltreatment beyond 240 miles.

⁸Specifically, we define these categories based on the quartiles of the travel distance distribution, as shown in Figure A1.

In Online Appendix Figure A3, we illustrate nonlinear trends by examining baseline travel distances of 0 miles, 62.7 miles (median), and 78.3 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, a 100-mile increase from 0 miles results in a 22.9% increase in child maltreatment, compared to increases of 16.4% and 14.8% from baselines of 62.7 miles and 78.3 miles, respectively. These findings support our 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).

Revisiting the first stage. While prior studies have established a negative association between travel distance and abortion rates (e.g., Myers 2024), we validate this finding using our sample and the regression specification in Equation (1). To assess this relationship, we replace the outcome variable with the abortion rate across counties over time. Figure A4 shows that abortions decline by approximately 19.3% ($p < 0.05$) for every 100-mile increase in travel distance. This finding aligns with Myers (2024), who report a 16% decline, despite differences in study periods and specifications.⁹

Importantly, our heterogeneity analysis reveals declines in abortion rates across all groups, with particularly pronounced declines in socioeconomically disadvantaged and rural areas. Consistent with existing literature, we also find a nonlinear relationship between travel distance and abortion rates. As shown in Table A3, the effect of travel distance on abortions diminishes at greater distances. We estimate the turning point at approximately 363 miles.¹⁰ These nonlinear relationships remain robust to the inclusion of state-by-year fixed effects.

⁹Given a mean abortion rate of 6.4 per 1,000 females aged 15–44, this translates to 1.24 fewer abortions per 100-mile increase in travel distance to the nearest clinic.

¹⁰The turning point is derived from the first derivative of the quadratic specification:

$$\frac{d \text{ Maltreatment}}{d \text{ Distance}} = \hat{\beta}_1 + 2\hat{\beta}_2 \times \text{Distance} = 0.$$

Solving for distance, we get:

$$\text{Distance} = -\frac{\hat{\beta}_1}{2\hat{\beta}_2}.$$

Using the estimates in column (1), we obtain:

$$-\frac{-0.305}{2 \times 0.042} \times 100 = 363 \text{ miles.}$$

Since distance is measured in 100-mile units, we multiply by 100.

Threats to identification. In alternative specifications of the child maltreatment regression, we also exploit within-state variation by including state-by-year fixed effects, which account for state-level policy changes and economic shocks over time. Despite this stringent control, which absorbs substantial variation, our estimates remain qualitatively robust, reinforcing the consistency of our findings (as shown in Table A2). To further address potential endogeneity concerns, we conduct additional robustness checks. For example, we test whether abortion facility closures—and the resulting increased travel distances—are driven by county abortion rates. Regressing travel distance to the nearest abortion facility in period $t + 1$ on abortion rates in period t (Table A4), we find no evidence of such a reverse feedback effect. While one marginally significant estimate in column (2) emerges, its negative sign contradicts the hypothesis that increased travel distances result from higher 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.¹¹ Note also that this estimation strategy alleviates concerns associated with TWFE, particularly when estimating the average level treatment effects.

We present our event study estimates in Figure A5. We find no evidence of a statistically significant pre-trend in child maltreatment, indicating that the counties were not experiencing differential trends in child maltreatment prior to the change in travel distance. In the post-change period, however, we observe increases in child maltreatment, particularly beginning two years after the travel distance increase and persisting into the third and fourth years. This pattern suggests a lagged effect, which is consistent with the timing of conception and childbirth, as well as the downstream mechanisms through which limited access may lead to increased maltreatment.

¹¹We 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.

4.1. Heterogeneous Effects

Heterogeneous effects by child characteristics. We next explore how the impact of abortion facility distance on child maltreatment varies by child race and gender. Figure 3 presents our baseline estimate alongside subgroup estimates. With respect to race, we find notable increases in maltreatment among both White and non-White children as travel distance increases, with more pronounced effects among non-White children. Specifically, a 100-mile increase in travel distance is associated with a 9.5% increase in child maltreatment among non-White children ($p < 0.05$). Regarding gender, both male and female children experience increases in maltreatment as travel distance rises, with the effect being more salient among females. In particular, females show a 10.6% increase ($p < 0.05$), while males exhibit a 7% increase ($p < 0.05$).

Heterogeneous effects by geographic characteristics. We examine how the impact of distance to the nearest abortion facility on child maltreatment varies by state policies and county characteristics. Figure 3 presents estimates by county-level poverty rate, minority population, rural population, and mandatory waiting laws. Our analysis yields several key findings: counties with above-median poverty rates and higher minority populations experience significant increases in child maltreatment—11.9% and 10.3%, respectively ($p < 0.05$). In contrast, wealthier and lower-minority counties show no significant changes. Counties with more rural populations also exhibit increased maltreatment, although the wider confidence intervals suggest these estimates are noisier. Additionally, states with mandatory waiting laws experience a 10.7% increase in child maltreatment rates ($p < 0.05$), suggesting that such laws may amplify the adverse effects of increased travel distance to abortion facilities.

Heterogeneous effects by maltreatment types. An additional key aspect of our analysis focuses on the types of child maltreatment contributing to the observed increase as travel distance increases. When we restrict the victim’s age to 1 year, the most common offenses are simple and aggravated assault, both classified as forms of physical abuse. Aggravated assault involves serious physical harm, often with the intent to cause significant injury, while simple assault entails minor physical harm, both qualifying as physical abuse but differing in severity.

In Figure A6, we explore changes in different forms of physical abuse against newborn children following an increase in travel distance. We observe a 6.3% increase ($p < 0.10$) in aggravated assaults as travel distance increases by 100 miles. Additionally, we find increases in simple assaults, though these are not statistically significant. Due to limited observations for several other categories of physical or emotional abuse, we aggregate them into a broader “physical (or emotional) abuse” category, which also includes simple and

aggravated assaults.¹² We find a pronounced increase in overall abuse when intimidation is included - an estimated 7.9% increase.¹³ We also observe marginally insignificant effects when including the most severe category of abuse, which is murder.

4.2. Alternative Data and Additional Heterogeneity Analyses

We use NCANDS data to investigate changes in alleged and substantiated child maltreatment cases as travel distance increases. Our key estimates are reported in Figure 4. For the total number of child maltreatment cases, our findings reveal a statistically significant positive effect of distance to the nearest abortion facility on alleged cases of maltreatment. Specifically, we observe a 3.2% increase ($p < 0.05$) in alleged cases as 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. For instance, alleged and substantiated cases of child maltreatment rise by 27% ($p < 0.05$) when caregivers face financial difficulties. When families experience inadequate housing at baseline, alleged maltreatment cases increase by approximately 48% ($p < 0.05$), while substantiated cases increase by 28% ($p < 0.05$).

In Figure A7, we further stratify our analysis by child race and find results consistent with our earlier analysis. For both total alleged and substantiated cases, increased travel distance is associated with higher rates of child maltreatment among both non-Hispanic White and non-White children. The increase in substantiated cases is particularly pronounced among Black and Hispanic children. Overall, we observe notable increases in both alleged and substantiated maltreatment across racial groups as travel distance rises.

The increase in child maltreatment associated with greater travel distance may be stronger among families where caregivers face physical or mental challenges, such as disability and behavioral problems (e.g., substance abuse, mental health issues), as the psychological strain of an unwanted birth could exacerbate these issues. However, as shown in Figure A8, we do not find any evidence supporting this hypothesis. It is also possible that individuals with physical or mental disabilities are less affected by abortion restrictions due to pre-existing barriers to access, and that there may be differential preferences for self-managed abortion (Biggs et al., 2023).

Next, we revisit the changes in maltreatment types as travel distance increases. While NIBRS data previously indicated rises in physical abuse, NCANDS data enable us to examine both physical abuse and neglect. In Figure A9, we find strong evidence of increased child neglect in both alleged and substantiated maltreatment cases as the

¹²We also explore changes in rape and sexual assault cases. However, the number of cases is too small to provide sufficient statistical power to detect changes when restricted to children aged one.

¹³Intimidation, a form of emotional abuse, involves behaviors that create fear, often without physical contact. For a one-year-old, subtle cues like tone, facial expressions, and body language can significantly impact their sense of security and emotional well-being, even if they do not fully understand language (Tronick et al., 1978; Cassidy and Shaver, 1999; Leclère et al., 2014).

proximity to the nearest abortion facilities decreases. Specifically, there is an approximate 29.3% increase ($p < 0.05$) in substantiated child neglect as travel distance increases by 100 miles. Supporting our initial findings, we also observe a 14.3% increase ($p < 0.05$) in substantiated physical abuse, which is qualitatively similar to, and quantitatively slightly larger than, the estimates based on NIBRS.¹⁴

4.3. Mechanisms

Increased travel distance to abortion facilities may impact child maltreatment through economic strain from unintended births. The costs of raising a child—healthcare, education, and daily care—can heavily strain family budgets, especially for unprepared families. This resource allocation challenge can lead to neglect or maltreatment. We use eviction filings as a measure of economic strain, assessing the income effect: the financial burden of unplanned children may exacerbate resource scarcity, increasing the risk of eviction if housing payments are missed.

In Figure A10, 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 15.4% ($p < 0.05$). We present the Poisson estimates for all our specifications in Online Appendix Table A5, with our baseline estimate highlighted in column (2). In the case of eviction filings, our analysis does not reveal strong evidence of nonlinear effects—the estimated coefficients on the squared terms are negative but statistically insignificant. Nonetheless, increased travel distance to abortion facilities is associated with a statistically significant rise in eviction filings. These effects remain robust in specifications that control for state-by-year fixed effects.

We further explore the impact of travel distance to abortion facilities on eviction filings, focusing on county characteristics. Our findings align with the heterogeneity analysis previously introduced. Counties with a higher proportion of women aged 18-44 in the second or third tertile experience increases in eviction filings by 14% ($p < 0.05$) and 16% ($p < 0.05$), respectively, per 100-mile increase in travel distance. Similarly, counties with above-median poverty or rural populations experience significant increases in evictions, which correlates with our earlier findings of higher child maltreatment rates in these areas. Departing from earlier findings, we observe similar increases in eviction filings across counties with both higher and lower minority populations. However, there is a non-negligible increase, approximately 15% ($p < 0.05$), in counties with higher minority populations.

¹⁴In this sense, using both datasets offers a bounding exercise: NCANDS captures a broader spectrum of maltreatment, including less severe cases, while NIBRS primarily reflects more serious incidents that result in police involvement and arrest. Together, they allow us to bracket the range of maltreatment outcomes across varying levels of severity.

5. Conclusion

In this paper, we study the impact of distance to the nearest abortion clinic on child maltreatment, focusing specifically on children under the age of one. Our findings reveal a significant increase in maltreatment cases, particularly child neglect and physical abuse, associated with increased travel distance to abortion facilities. According to our results, child maltreatment increases by 8.5% in response to a 100-mile increase in the travel distance to the nearest abortion clinic. With a mean maltreatment rate of 0.169 per 1,000 children, this translates into an additional 0.014 victims of maltreatment per 1,000 children. Put differently, given a 100-mile increase in travel distance to the nearest abortion clinic, for every abortion deterred among 1,000 women aged 15-44, there is an additional 0.012 (0.014/1.240) child maltreatment victim per 1,000 children.

These results imply that restricted access to reproductive health services may contribute 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 \$73,742 per child.¹⁵ Based on the NCANDS estimates, the cost could exceed \$234,000, particularly for families facing financial difficulties at baseline. Therefore, our analysis indicates the importance of accessible reproductive health services and their relation to child welfare.

Our paper offers several policy insights. First, findings show that maltreatment challenges are most acute during infancy, when the impacts of unintended parenthood are immediate. This highlights the importance of accessible reproductive health services and policies supporting family planning and birth spacing to prevent child maltreatment, emphasizing the link between reproductive healthcare and child welfare.

Second, the racial disparities we document between abortion access and child maltreatment suggest that restricting abortion services could exacerbate societal inequities, particularly among vulnerable groups. Reproductive healthcare must be integral to social policies aimed at reducing racial disparities.

Furthermore, economic conditions also play a crucial role in moderating the relationship between abortion access and child maltreatment. In economically

¹⁵Earlier studies estimate the lifetime economic burden of child maltreatment to be \$592 billion (Klika, Rosenzweig, and Merrick, 2020). Using this cost estimate, we calculate the base cost per child as \$592 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:

$$\underbrace{\$867,558}_{\text{Base Cost}} \times \underbrace{0.085}_{\% \text{ Increase}} = \$73,742.$$

As previously noted, our first-stage analysis indicates that the abortion rate is reduced by 15% in response to a 100-mile increase in the travel distance to the nearest abortion clinic, which corresponds to 0.96 fewer abortions per 1,000 women aged 15-44.

disadvantaged areas, limited access to reproductive health services deepens socioeconomic challenges, increasing the risk of child maltreatment. Policies must account for these economic realities, moving beyond one-size-fits-all solutions.

Lastly, effective interventions could include family support programs offering economic assistance, childcare, and education, as well as improved transportation infrastructure or subsidized travel for medical care. Long-term solutions should focus on fostering economic growth through job creation, education, and community development. Integrating these considerations into reproductive healthcare policies can address immediate needs while promoting broader family and child well-being.

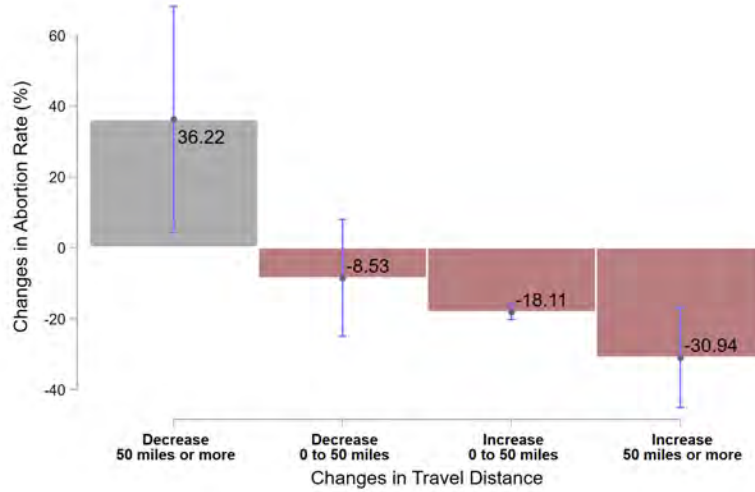
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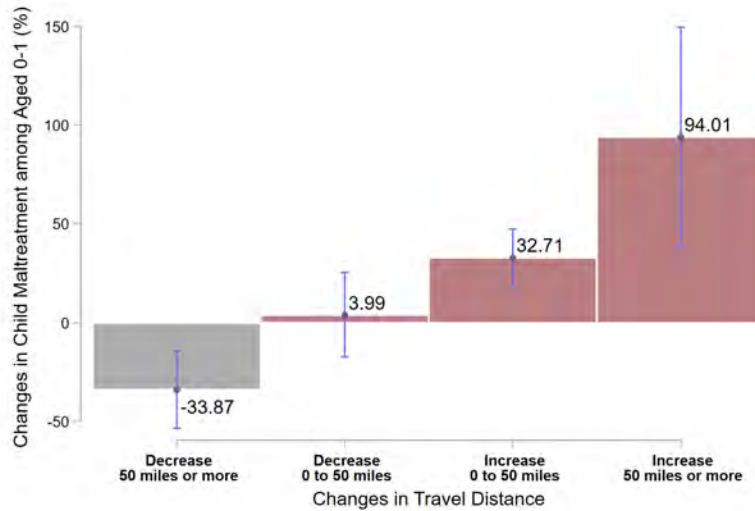
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(a) Changes in the Abortion Rate



(b) Changes in Child Maltreatment

Figure 1. Relationships Between Travel Distance, Abortion Rates, and Child Maltreatment

Notes: The top panel shows the correlation between changes in the abortion rate and changes in travel distance over the study period. The bottom panel shows the correlation between changes in child maltreatment among children aged one year or younger and changes in travel distance. Changes in outcomes, Y , are calculated as $\frac{Y_{2018}-Y_{2011}}{Y_{2011}} \times 100\%$. The change in travel distance is measured as the difference in travel distance between 2010 and 2017.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Incident-Based Reporting System (NIBRS). The abortion rate data are also from Myers (2024).

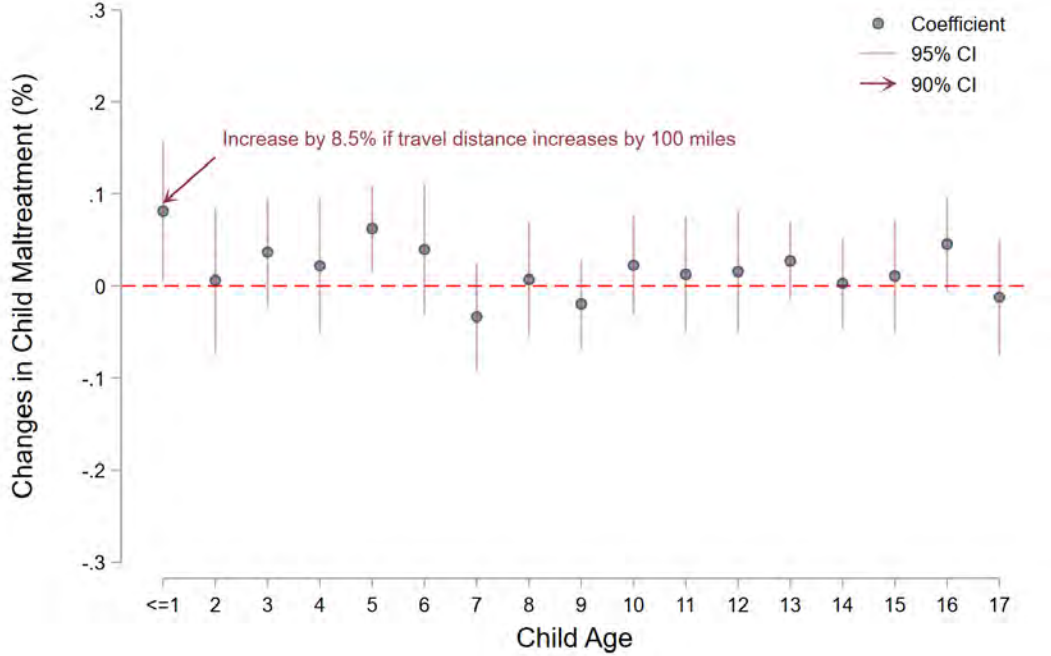


Figure 2. Effects of Abortion Facility Distance on Child Maltreatment by Age

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. Specifically, we account for agency fixed effects, year fixed effects, county demographics, and state-level policy or economic measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

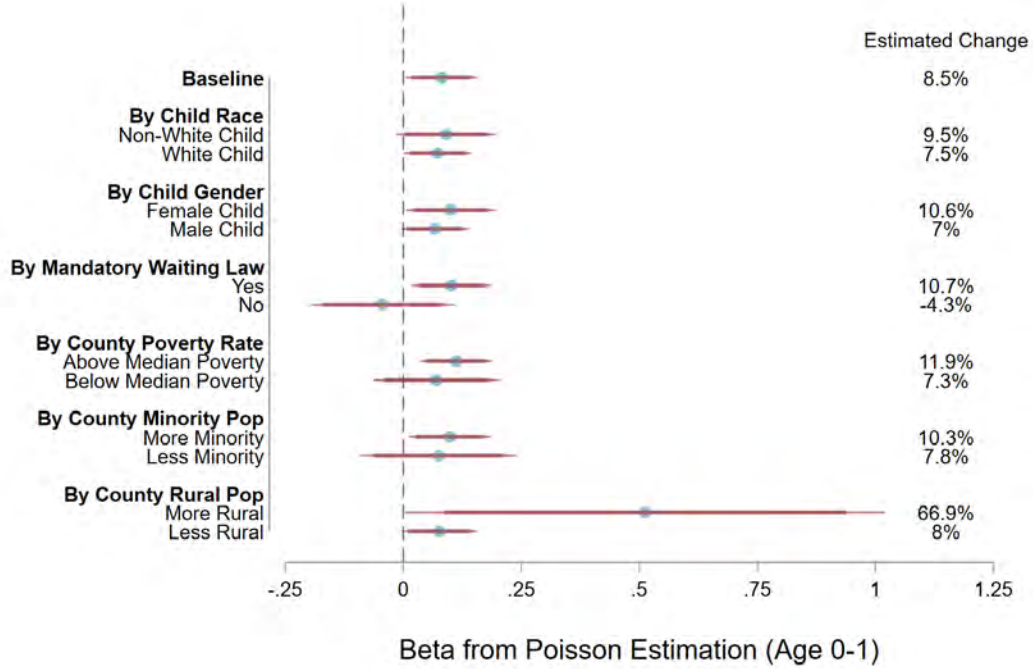


Figure 3. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment

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. Specifically, we account for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

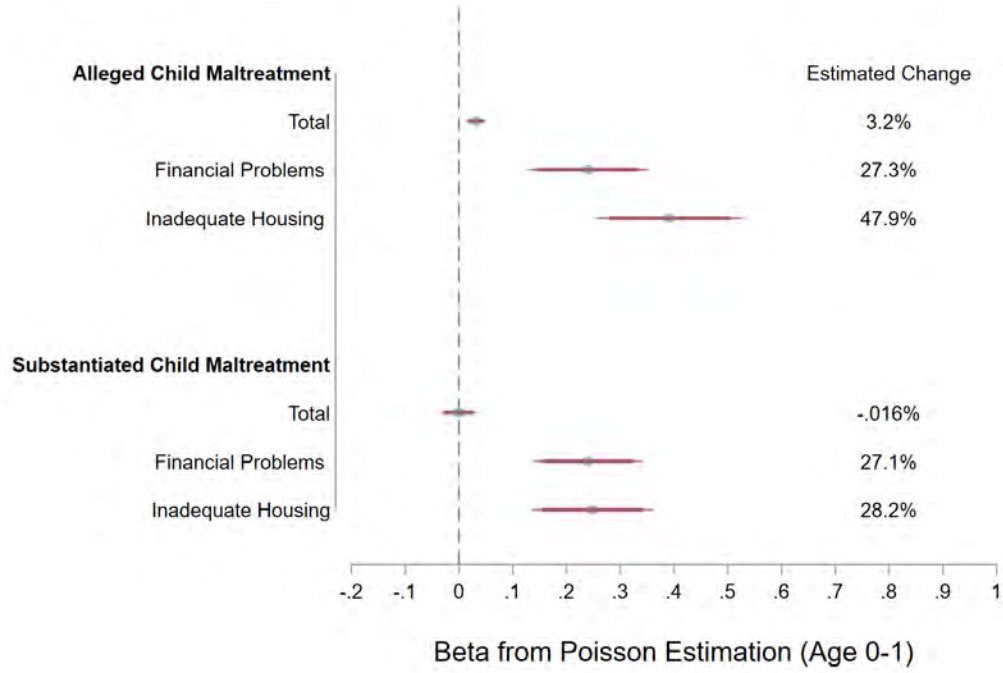


Figure 4. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Caregiver Risk Factors, NCANDS

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. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Child Abuse and Neglect Data System (NCANDS). We report the sources for control variables in the [Other Covariates](#) section.

Online Appendix

Other Covariates

We supplement our analytical data with various county and state characteristics. At the county level, we integrate demographic and socio-economic factors. Specifically, we derive the proportions of white and Hispanic females aged 15 to 44 (capturing both race and ethnic characteristics), the percentage of children under 19, and the average age from the Surveillance, Epidemiology, and End Results (SEER) Program. We source data on median household income and the poverty rate for children under 18 from the U.S. Census Bureau’s Small Area Income and Poverty Estimates (SAIPE), and data on the unemployment rate from the Bureau of Labor Statistics’ Local Area Unemployment Statistics (LAUS). Additionally, we calculate the number of psychiatric treatment facilities per capita using data from the U.S. Census Bureau’s County Business Patterns.¹⁶ We obtain the proportion of urban population at the county level from Myers (2024).

Earlier studies suggest that congestion at facilities that remain open 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 as documented in the Myers database.¹⁷

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). We also include economic support indicators, such as minimum wage, maximum welfare benefits for three-person families, state Medicaid enrollment rate, and state total output measured by GDP derived from the UKCPR National Welfare Data (UKCPR, 2023). In our most conservative specification, we account for these policy changes by including state-by-year fixed effects.

¹⁶Although 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.

¹⁷The average service population essentially measures the number of women aged 15-44 served per clinic in a region (Lindo et al., 2020).

Appendix Figures and Tables

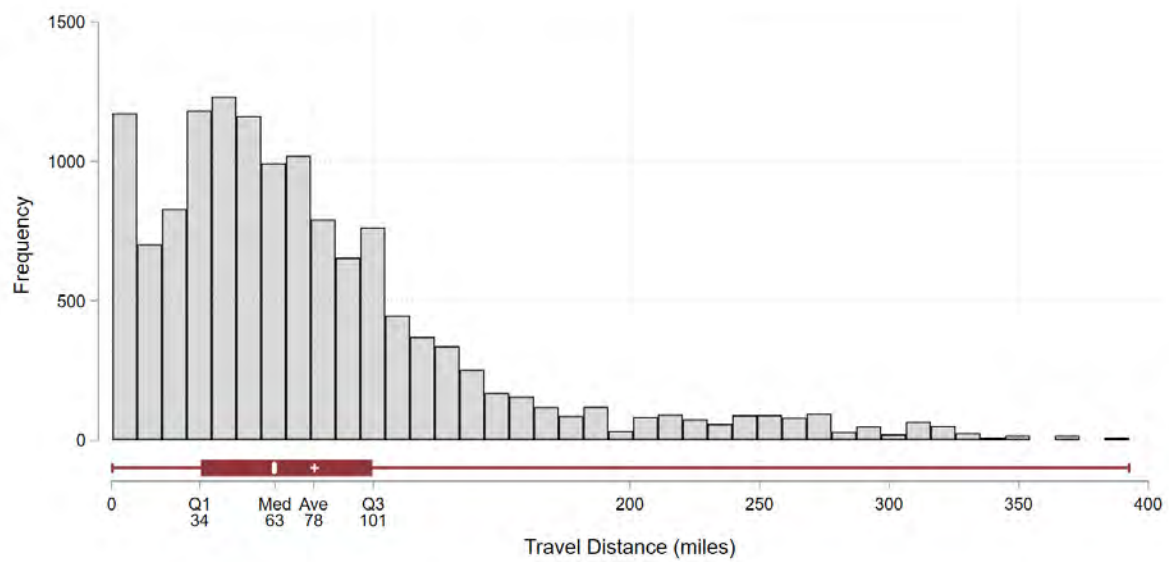


Figure A1. Histogram of Abortion Facility Distance

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.

Data Sources: Myers Abortion Facility Database ([Myers, 2024](#)).

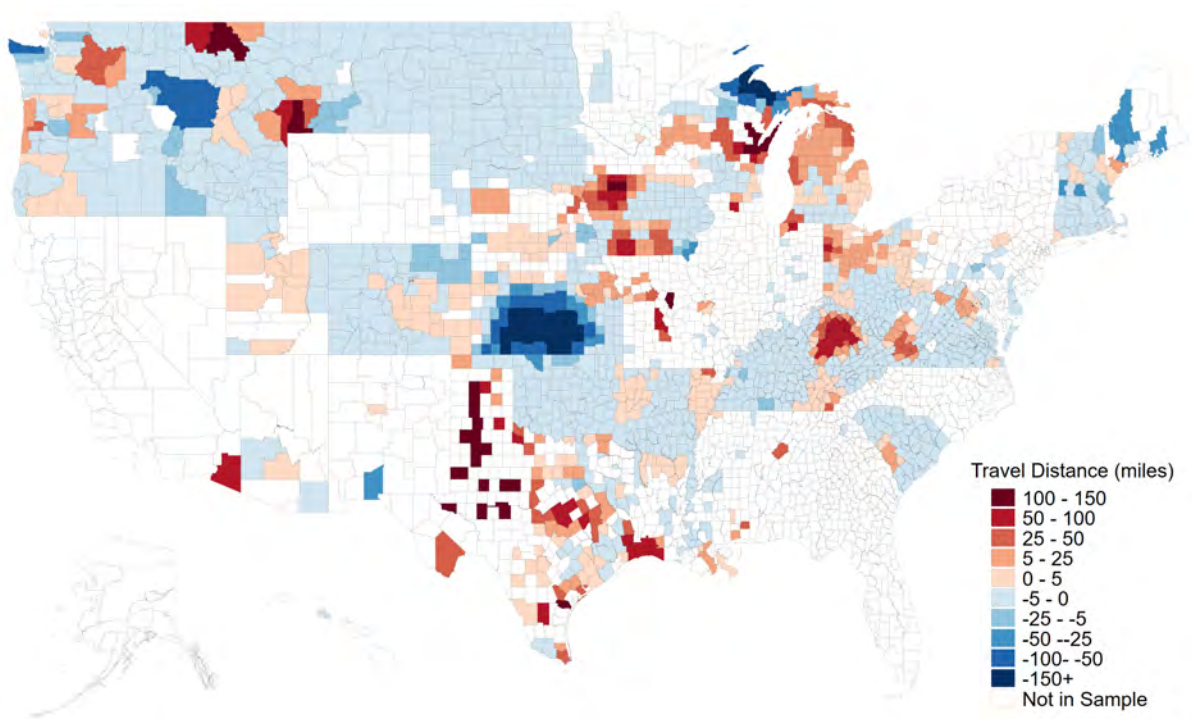


Figure A2. Variation in Abortion Facility Distance

Notes: This figure illustrates the geographic changes in travel distance to the nearest abortion facility within our analytical sample between 2010 and 2017. A positive (negative) value indicates an increase (decrease) in travel distance over this period.

Data Sources: Myers Abortion Facility Database ([Myers, 2024](#)).

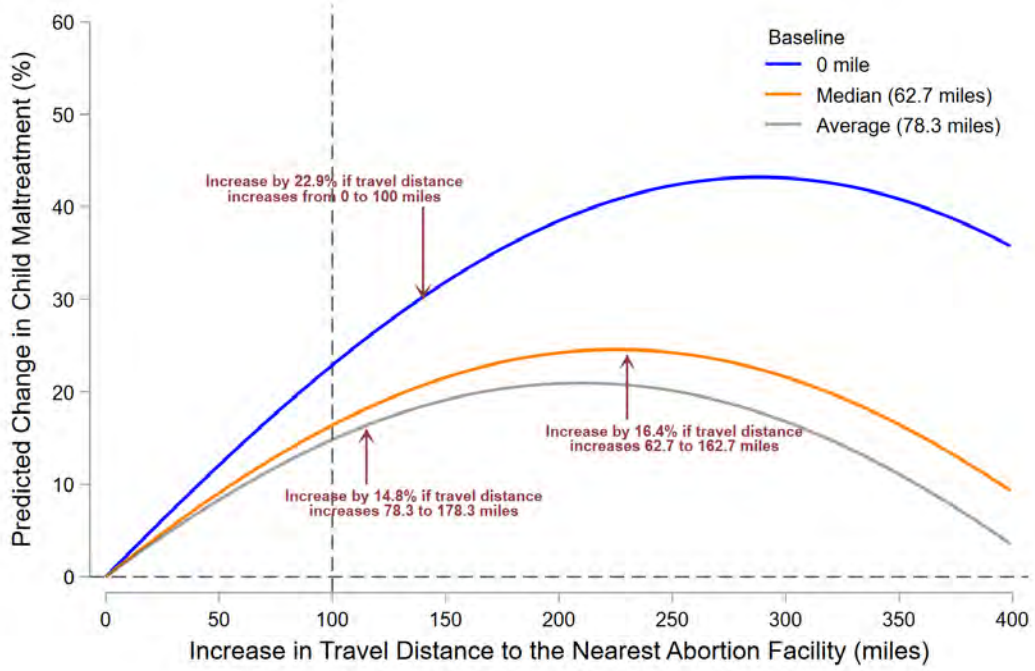


Figure A3. Nonlinear Effects of Abortion Facility Distance on Child Maltreatment

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 A2. We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

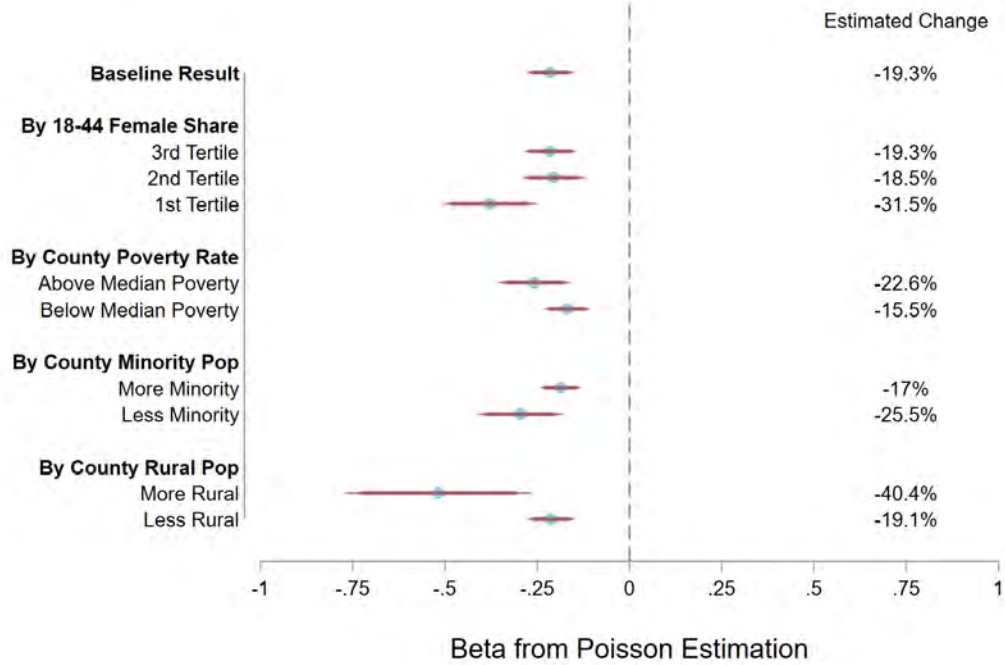


Figure A4. Heterogeneous Effects of Abortion Facility Distance on the Abortion Rate

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the county-level abortion rate, alongside the associated 90% and 95% confidence intervals, by child race, gender, or county characteristics. Abortion is measured in period $t + 1$, while changes in abortion facility distance are measured in period t . The analysis employs a Poisson model with the population of women aged 15 to 44 as an exposure. Specifically, we account for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024). The abortion rate data are also from Myers (2024). We report the sources for control variables in the [Other Covariates](#) section.

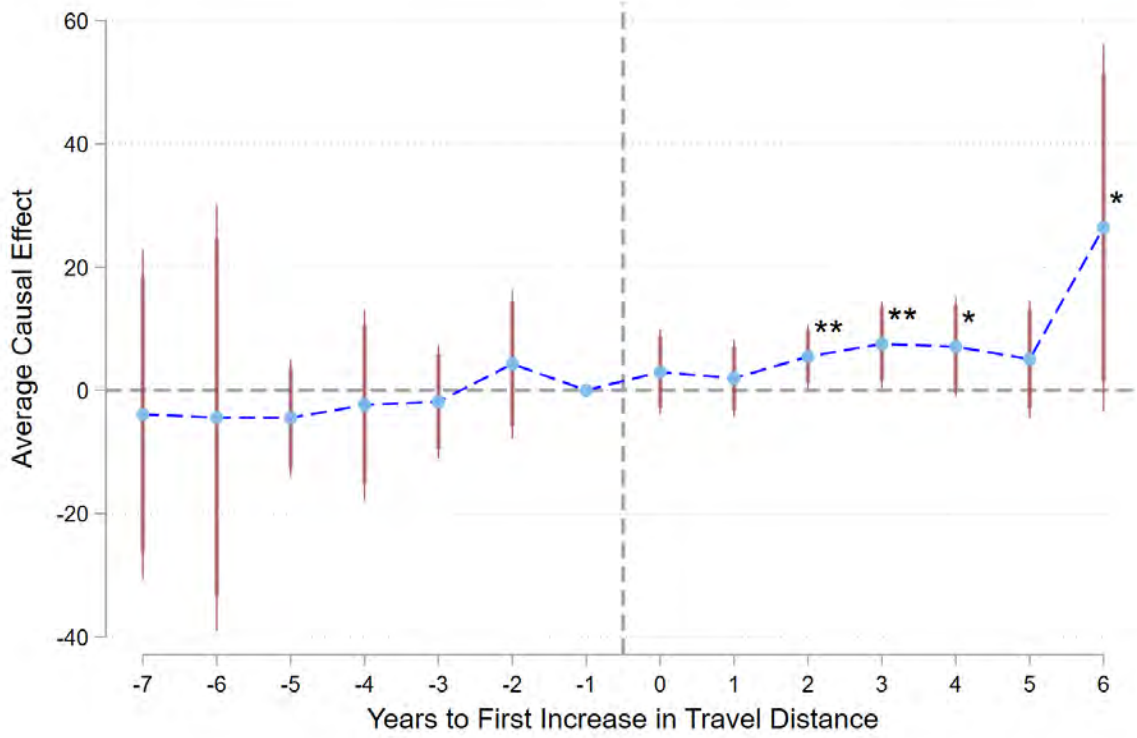


Figure A5. Effects of Abortion Facility Distance on Child Maltreatment: Event Study

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. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data Sources: Myers Abortion Facility Database ([Myers, 2024](#)) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

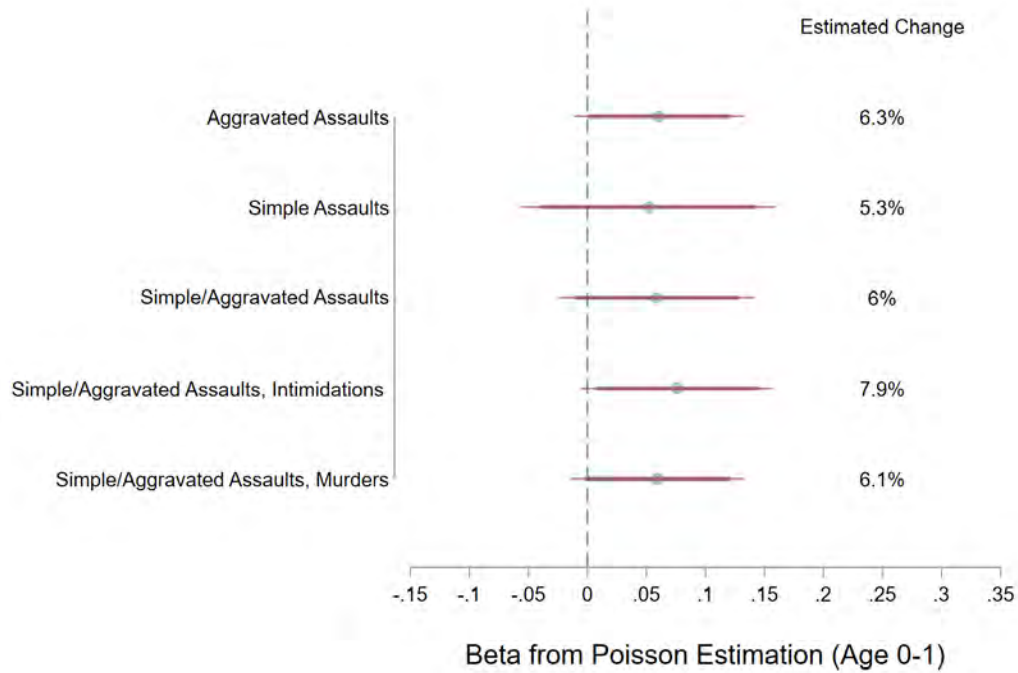


Figure A6. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Child Maltreatment Types, NIBRS

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 child maltreatment data from the NIBRS. The primary outcome is the incidence of different types 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. The analysis accounts for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

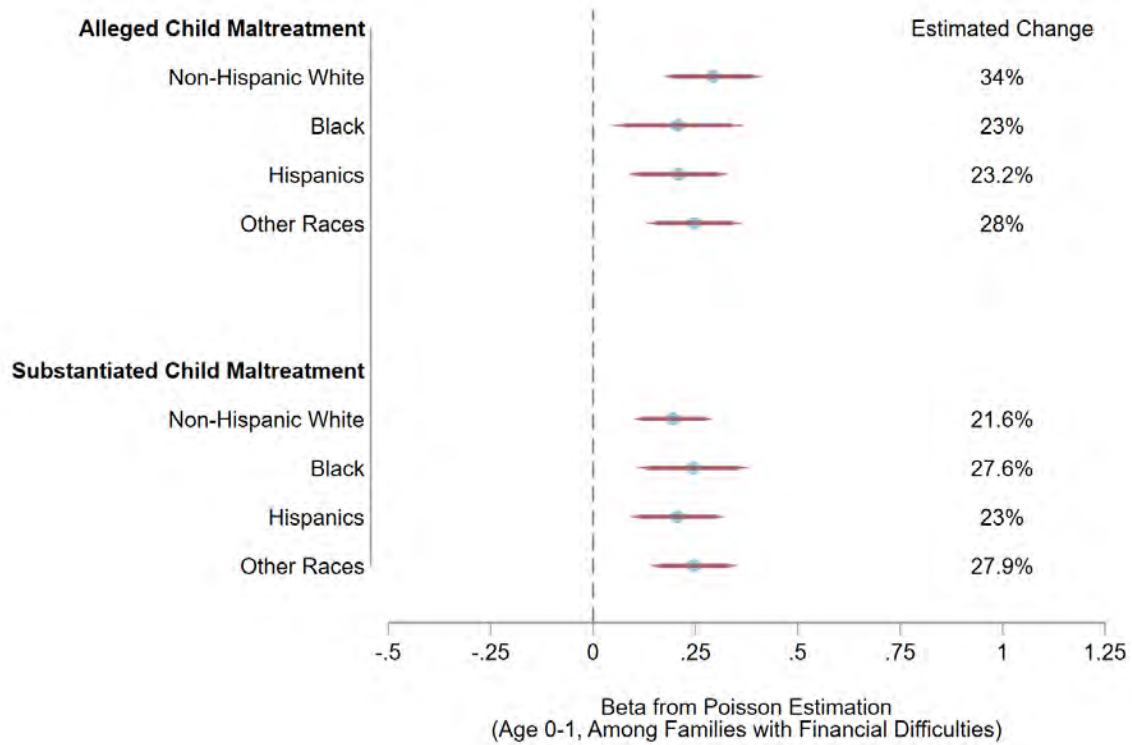


Figure A7. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Racial Characteristics, NCANDS

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. 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. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Child Abuse and Neglect Data System (NCANDS). We report the sources for control variables in the [Other Covariates](#) section.

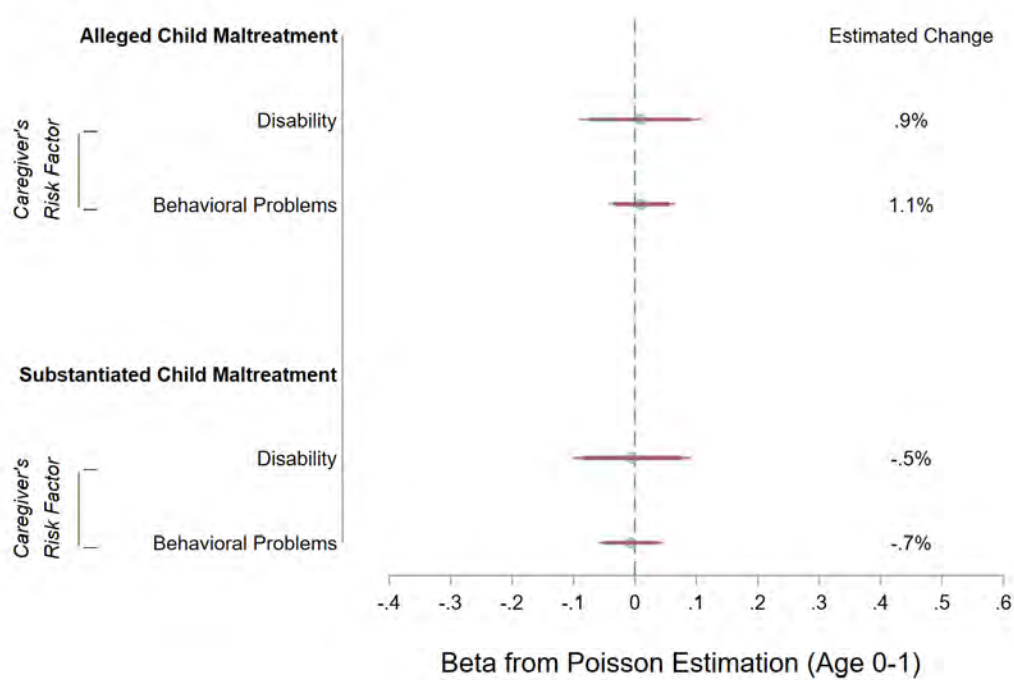


Figure A8. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Additional Caregiver Risk Factors, NCANDS

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. The analysis accounts for county fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Child Abuse and Neglect Data System (NCANDS). We report the sources for control variables in the [Other Covariates](#) section.

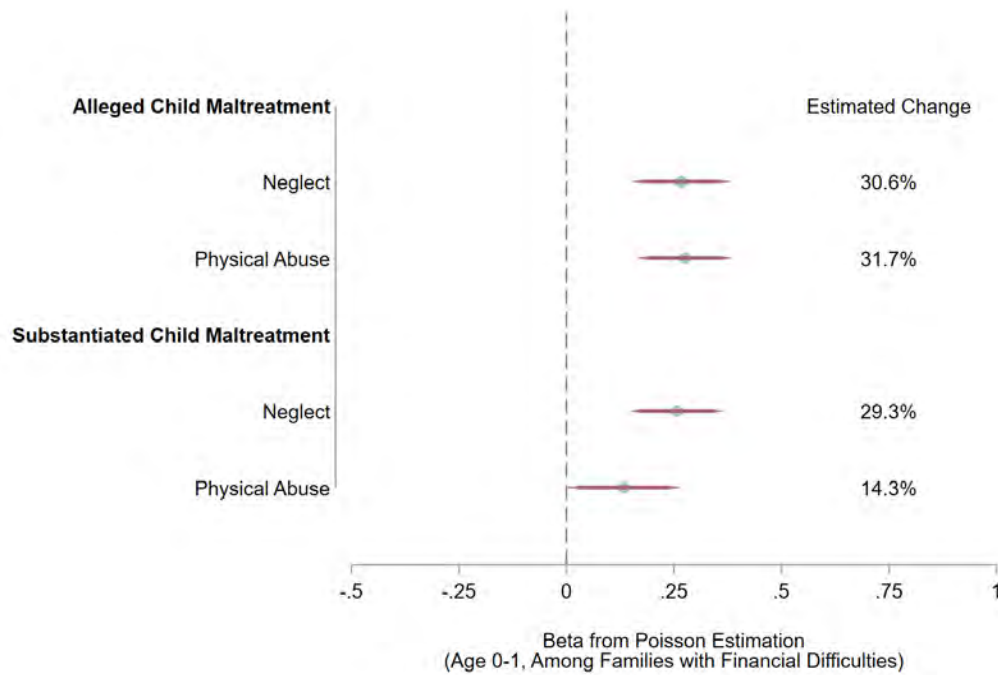


Figure A9. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment: Child Maltreatment Types, NCANDS

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. The primary outcome is the incidence of different types 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. The analysis accounts for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & National Child Abuse and Neglect Data System (NCANDS). We report the sources for control variables in the [Other Covariates](#) section.

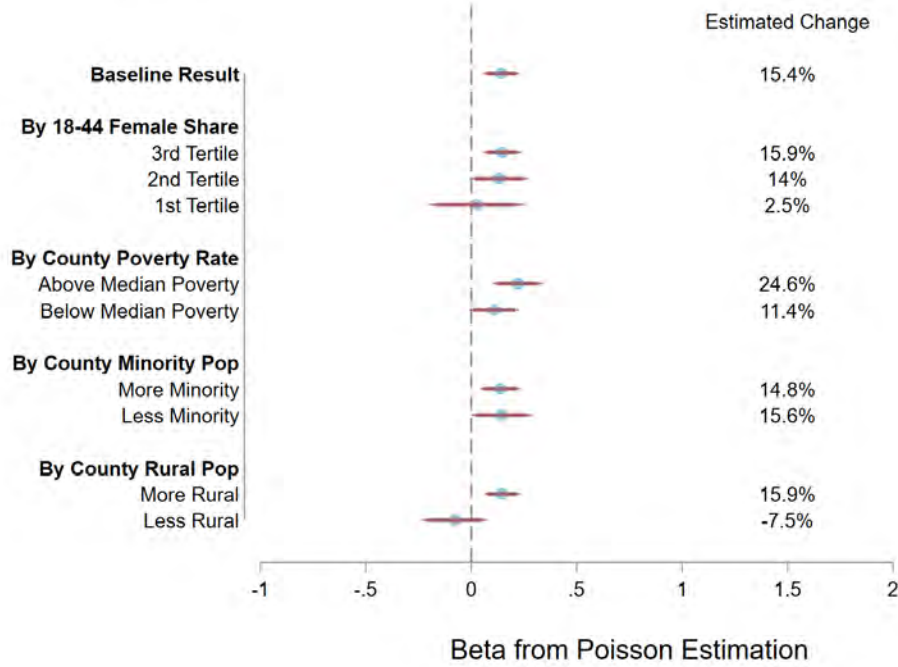


Figure A10. Heterogeneous Effects of Abortion Facility Distance on Evictions

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. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). We convert Poisson estimates to percentage changes using the transformation: $(\exp(\hat{\beta}) - 1) \times 100\%$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & Eviction Lab Data (Gromis et al., 2022). We report the sources for control variables in the [Other Covariates](#) section.

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

Year (1)	Agencies (2)	Counties (3)	States (4)
2011	4,318	1,429	35
2012	4,595	1,439	35
2013	4,645	1,442	35
2014	4,679	1,448	35
2015	4,747	1,453	35
2016	4,984	1,479	36
2017	5,037	1,511	39
2018	5,146	1,575	40
Unique Obs.	6,021	1,691	41

Notes: Calculated by the authors using processed NIBRS data (2011-2018).

Table A2. Nonlinear Impact of Abortion Facility Distance on Child Maltreatment: NIBRS

	Child Maltreatment (Children Aged 0-1)			
	(1)	(2)	(3)	(4)
Distance (100 miles)	0.125** (0.063)	0.075 (0.076)		
Distance (100 miles) Squared	-0.011 (0.014)	-0.002 (0.014)		
Distance: 30-60 miles			0.072 (0.063)	0.054 (0.083)
Distance: 60-120 miles			0.264*** (0.094)	0.337** (0.144)
Distance: 120-240 miles			0.294** (0.116)	0.249* (0.150)
Distance: 240+ miles			0.318 (0.217)	0.346 (0.281)
N	38153	38153	38153	38153
Dep. Var. Mean (per 100,000 children)	16.954	16.954	16.954	16.954
Agency FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
County Demographic	✓	✓	✓	✓
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 . Across all specifications, we account for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data Sources: Myers Abortion Facility Database ([Myers, 2024](#)) & National Incident-Based Reporting System (NIBRS). We report the sources for control variables in the [Other Covariates](#) section.

Table A3. Nonlinear Impact of Abortion Facility Distance on the Abortion Rate

	County-Level Abortion Rate			
	(1)	(2)	(3)	(4)
Distance (100 miles)	-0.305*** (0.057)	-0.259*** (0.055)		
Distance (100 miles) Squared	0.042*** (0.021)	0.030 (0.020)		
Distance: 30-60 miles			-0.057*** (0.022)	-0.051*** (0.018)
Distance: 60-120 miles			-0.174*** (0.029)	-0.145*** (0.027)
Distance: 120-240 miles			-0.297*** (0.060)	-0.277*** (0.059)
Distance: 240+ miles			-0.501*** (0.092)	-0.458*** (0.092)
N	16631	16631	16631	16631
Clusters	2258	2258	2258	2258
Dep. Var. Mean (per 1,000 females aged 15-44)	6.391	6.391	6.391	6.391
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
County Demographic	✓	✓	✓	✓
State Policy Measures	✓	✓	✓	✓
State × Year FE		✓		✓

Notes: This table presents the impact of travel distance to the nearest abortion facility on the county-level abortion rate. Abortion is measured in period $t + 1$, while changes in abortion facility distance are measured in period t . The analysis employs a Poisson model with the population of women aged 15 to 44 as an exposure. Across all specifications, we account for agency fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data Sources: Myers Abortion Facility Database (Myers, 2024). The abortion rate data are also from Myers (2024). We report the sources for control variables in the [Other Covariates](#) section.

Table A4. 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)	-0.00062 (0.00175)	-0.00423** (0.00187)	0.00075 (0.00108)	-0.00112 (0.00109)	0.00067 (0.00093)	-0.00055 (0.00101)	0.00008 (0.00059)	-0.00085 (0.00069)
N	16446	16446	16446	16446	16446	16446	16446	16446
Clusters	2144	2144	2144	2140	2144	2144	2144	2144
Dep. Var. Mean	0.086	0.086	0.038	0.038	0.021	0.021	0.010	0.010
County FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
County Demographics	✓	✓	✓	✓	✓	✓	✓	✓
State Policy Measures	✓		✓		✓		✓	
State \times 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 . Across all specifications, we account for county fixed effects, year fixed effects, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data Sources: Myers Abortion Facility Database ([Myers, 2024](#)). The abortion rate data are also from [Myers \(2024\)](#). We report the sources for control variables in the [Other Covariates](#) section.

Table A5. Nonlinear Impact of Abortion Facility Distance on Eviction Filings

	Eviction Filings			
	(1)	(2)	(3)	(4)
Distance (100 miles)	0.166 (0.104)	0.194* (0.103)		
Distance (100 miles) Squared	-0.012 (0.042)	-0.005 (0.040)		
Distance: 30-60 miles			0.009 (0.042)	0.034 (0.037)
Distance: 60-120 miles			0.126** (0.058)	0.148*** (0.058)
Distance: 120-240 miles			0.205*** (0.055)	0.238*** (0.082)
Distance: 240+ miles			0.333* (0.171)	0.471** (0.231)
N	19626	19626	19626	19626
Clusters	2850	2850	2850	2850
Dep. Var. Mean (per 100 households)	3.226	3.226	3.226	3.226
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, county demographics, and state-level policy measures. The county demographics include the share of white females aged 15-44, the share of Hispanic females aged 15-44, the percentage of children under 19, average age, median household income, the poverty rate for children under 18, the unemployment rate, the number of psychiatric treatment centers per capita, the share of urban population, and the average service population in the destination county. The state-level policy or economic measures include mandatory abortion waiting periods, minimum wage, maximum welfare benefits for three-person families, Medicaid enrollment rate, and state output (measured by GDP). Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data Sources: Myers Abortion Facility Database (Myers, 2024) & Eviction Lab Data (Gromis et al., 2022). We report the sources for control variables in the [Other Covariates](#) section.