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Proximity to Abortion Services and Child Maltreatment

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Abstract

This study provides a comprehensive analysis of the causal 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 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 20.8% increase in maltreatment reports. This effect is particularly pronounced for very young children, non-white children, and those living in poverty-stricken, racially diverse, and rural areas. Supplemental analyses using data from the National Data Archive on Child Abuse and Neglect (NDACAN) 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 provide a deeper understanding of the complex interplay between reproductive health services access, socio-economic factors, and child welfare.

Keywords: Child Maltreatment, Travel Distance, Reproductive Services, Abortion, 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 those abused or neglected lost an estimated 1,990 lives (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; 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. 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 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.[1] 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 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

[1]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.

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 agency and child files from the National Child Abuse and Neglect Data System (NDACAN) between 2011 and 2022. The agency file provides state-specific information on all reported cases of maltreatment investigated by state child protective service agencies. On the other hand, the child file consists of information on investigations into alleged child maltreatment, including demographics of children and perpetrators, types of maltreatment, investigation outcomes, risk factors for both children and caregivers, and services rendered post-investigation. This comprehensive dataset enables us to dive deeper into the various forms of maltreatment experienced by children due to obstacles in adoption services. Importantly, 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 20.8% 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 old 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 indicate discernible 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 peers. 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 that helps accurately understand victimization and offending. It captures comprehensive details about the characteristics

of each crime incident, including a broad array of offenses (simple assault, property crime, violent crime, 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.

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. 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.

To ensure compatibility with the NIBRS data, we use the Myers dataset for the years 2010 to 2017. 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 data using the county identifier.

2.3. Eviction Case Filings

The county-level number of eviction case filings data is sourced from Gromis et al. (2022) aggregated over 73.2 million individual eviction records covering 48 states and DC from LexisNexis Risk Solutions. These proprietary data was compiled through electronic court record requests or manual courthouse file reviews. The legal eviction process starting with the filing of an eviction lawsuit in court could end up with different consequences, such as uncontested tenant departures to court-mandated evictions, or dispute resolutions that allow tenants to stay. Typically spanning several months, this legal process often creates multiple legal event records associated with each case filing. Gromis et al. (2022) aggregate the individual eviction records to the case level using probabilistic (inexact) matching across tenant names and addresses listed in the individual records and excluded filings against commercial properties. In our study, we use their eviction case filing data from 2011 to 2018, including variables such as number of eviction case filings and total number of household renting a property in a county.

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 as follows: 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 is sourced from the U.S. Census Bureau's Small Area Income and Poverty Estimates (SAIPE); the unemployment rate is obtained from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS); and the count of psychiatric treatment facilities, calculated using data from the U.S. Census Bureau's County Business Patterns. Additionally, we include data on the number of abortion facilities and the log-transformed average service population within each county, as documented in the Myers database.

On the state level, our dataset incorporates legislative and policy variables that could influence abortion access. The mandatory abortion waiting period policy data are sourced from Myers (2021); information on parental involvement laws is obtained from Myers (2022). We also include economic support indicators, such as the maximum food stamp benefits for a three-person family and Earned Income Tax Credit (EITC) refund statuses, derived from the UKCPR National Welfare Data (UKCPR, 2023).

2.5. Descriptive Evidence

Our final analytical sample consists of 38,827 agency-year observations. The average child maltreatment is 3.87 per 100,000 population, with a standard deviation of 21.72.

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 left-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. 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 elucidates 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 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. For county-level controls, we include the percentage of white females aged 15 to 44, the percentage of children under 17, the log-transformed median household income, the unemployment rate, and the number of psychiatric treatment facilities. On the state level, we include policy measures such as mandatory abortion waiting periods, parental involvement laws, the maximum food stamp benefits for a three-person family, and Earned Income Tax Credit (EITC) refund statuses. Additionally, we account for the number of abortion facilities and the log-transformed average service population within the destination county. 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.

As illustrated by Callaway, Goodman-Bacon, and Sant'Anna (2024), when the treatment is continuous, we need a strong version of parallel trends assumption to identify the causal effect of a small change in the "dose", which is referred to as the average causal response (ACR) and can be represented by $ACR = \int_{d_{min}}^{d_{max}} \frac{\partial ATE(d)}{\partial d}$. To identify the ACR to travel distance in our context, that is, the causal effect of one-mile change in the travel distance on child maltreatment, we need a strong conditional parallel trend assumption as described below for our regression model in Equation (1):

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

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. While this strong version of the parallel trends assumption is not directly testable, it is crucial to note that the assumption may be compromised if the changes in travel distance are not entirely exogenous. Myers (2024) offers compelling anecdotal evidence indicating that supply-side abortion policies primarily influence the openings and closures of abortion facilities, thereby affecting the travel distance to abortion services.[2]

Drawing on insights from Myers (2024), we provide additional evidence indicating that the abortion rate in the preceding year does not strongly predict changes in travel distance to the nearest abortion service in the subsequent year. This finding supports Myers (2024)'s assertion that the policy shocks driving the changes in travel distance were not closely related to demand-side factors.

In continuous treatment settings, Callaway, Goodman-Bacon, and Sant'Anna (2024) demonstrate that the strong parallel trends assumption helps in mitigating selection bias caused by potential heterogeneous treatment effects of the same treatment dose across different groups. Although directly testing this assumption is challenging, we leverage the heterogeneity-robust estimator developed by Callaway and Sant'Anna (2021) to alleviate our concerns regarding the undesirable consequences of treatment effect heterogeneity.

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 employs a flexible approach regarding the functional form of travel distance, exploring both linear and nonlinear effects. In our most comprehensive 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 20.8% ($p < 0.05$) in column (2).[3] In columns (3) and (4), 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, although the decline in the slope is statistically insignificant in some specifications. A similar pattern emerges when

[2] Myers (2024) demonstrates that facility closures and increases in travel distance predominantly occur in states with more stringent supply-side abortion policies, such as the "Targeted Regulation of Abortion Providers." Conversely, facility openings and decreases in travel distance are more common in states with policies that support abortion rights, for instance, those expanding the capacity of abortion clinicians to perform abortions.

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

we classify travel distance to the nearest abortion facility using ordered ranges (i.e., 50-100 miles, 100-150 miles, 150-200 miles, and 200+ miles). Particularly in column (6), using our most comprehensive specification, we identify a salient hump-shaped relationship, indicating increases in child maltreatment but at a decreasing rate after 200 miles.

In Appendix Figure A2, we visually illustrate these nonlinear trends by considering various baseline travel distances. Specifically, we plot the nonlinear effects of distance to the nearest abortion facility on child maltreatment, starting from baselines of 0 miles, 34.5 miles (first quartile), 63 miles (second quartile), and 101.4 miles (third quartile). The visual representation clearly shows a nonlinear trend with increasing travel distance; however, the magnitude of change in child maltreatment decreases as the baseline travel distance increases. For example, an increase of 100 miles from a baseline of 0 miles results in an 80.6% increase in child maltreatment, whereas the same increase from a baseline of 101.4 miles (third quartile) results in a 35.7% increase. This pattern of diminishing increases in child maltreatment with longer baseline distances further supports existing literature that highlights a nonlinear relationship between abortion facility distance and both 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 A3, 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 our initial hypothesis.

In a similar vein, we address another concern: that counties experiencing changes in the distance to abortion facilities may differ from those without such changes in ways that could also correlate with our potential outcome. To investigate this concern, we conduct an event study analysis to compare pre-trends between counties before 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.[4]

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.

4.1. Heterogeneous Effects

Child maltreatment along the age dimension. We explore the changes in child maltreatment in period $t+1$ as the travel distance to the nearest abortion varies in period t. We expect this relationship to be particularly pronounced for newborn children under one year of age. In Figure 2, using our more comprehensive specification, 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.

While not altering the overarching narrative, we note decreases in child maltreatment at ages 7 and 13, corresponding to important developmental milestones. By age 7, most children attend the first or second grade of primary school, a phase marked by significant advancements in cognitive, emotional, and social development. Age 13 represents a pivotal period, as children transition into adolescence, characterized by substantial physical, emotional, cognitive, and social transformations. Several potential factors could contribute to the reduction of child maltreatment at these ages, including greater autonomy and an enhanced capacity for self-advocacy, increased social and institutional support, heightened parental engagement, and a renewed focus from parents on guiding their children through these pivotal changes. However, when we group together ages above one year, we do not consistently find a statistically significant effect across all specifications. Specifically, Appendix Table A2 presents estimates for our linear, quadratic, and categorical distance measures for children aged 2-6, 7-12, and 13-17. Most of these estimates are statistically insignificant. Notably, for the age group 7-12, we

[4]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.

also do not observe statistically significant reductions in child maltreatment in Panel C, column (4), which categorizes distance into four groups and accounts for state-by-year fixed 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 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 25.2% among non-White children ($p < 0.05$). 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 females than males. In particular, females exhibit a 22% increase in child maltreatment ($p < 0.10$), while males show a 19% 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 28.5% 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 13.9% ($p < 0.10$) and 20.1% ($p < 0.05$), 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 25.2% 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. Mechanisms

Multiple potential pathways could 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 4, 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 A4, 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. 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 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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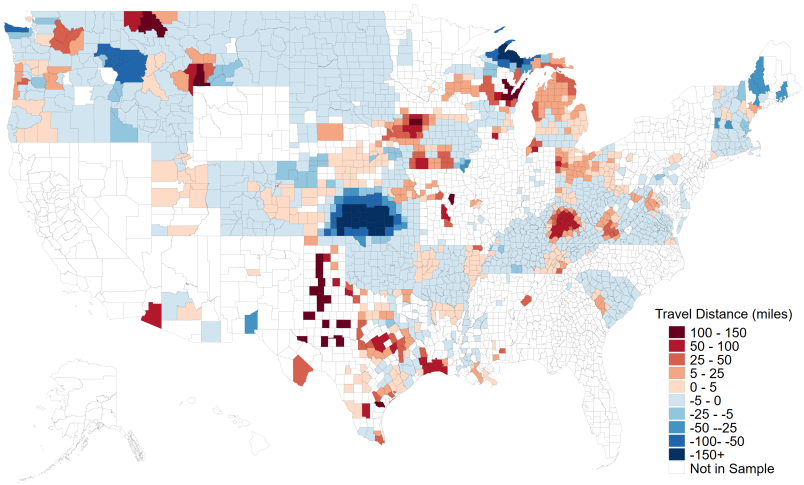
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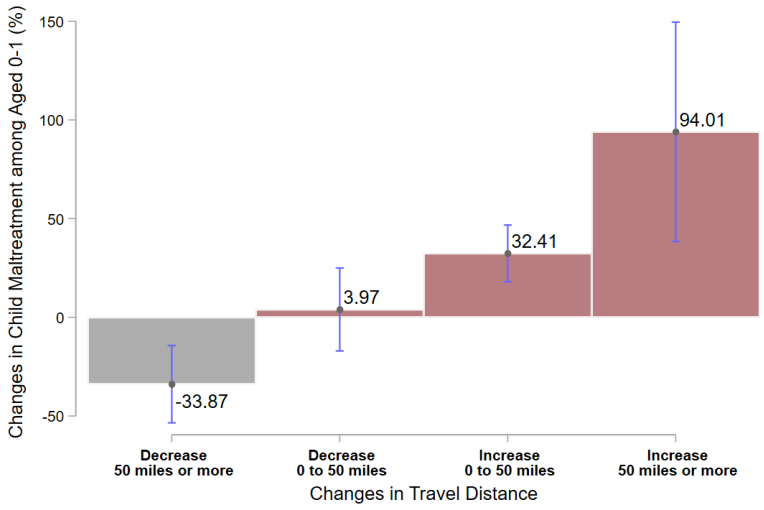
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(a) Change in Travel Distance to the Nearest Abortion Facility between 2010 and 2017



(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.

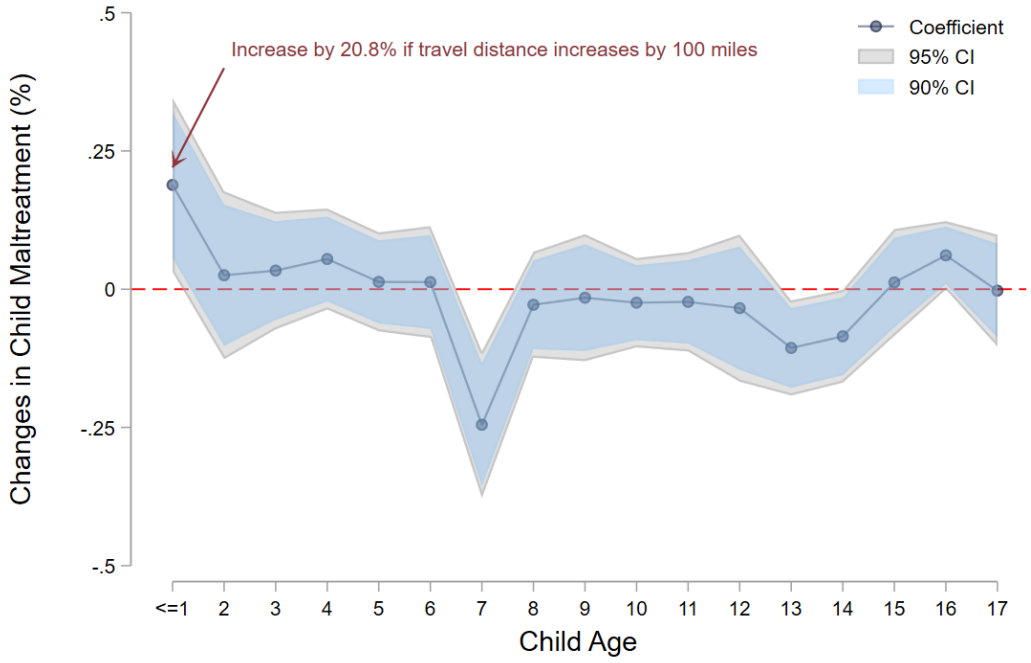


Figure 2. Effects of Abortion Facility Distance on Child Maltreatment by Age

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment for children by child age. 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 (2) in Table 1. Specifically, we account for county fixed effects, year fixed effects, state-by-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, the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

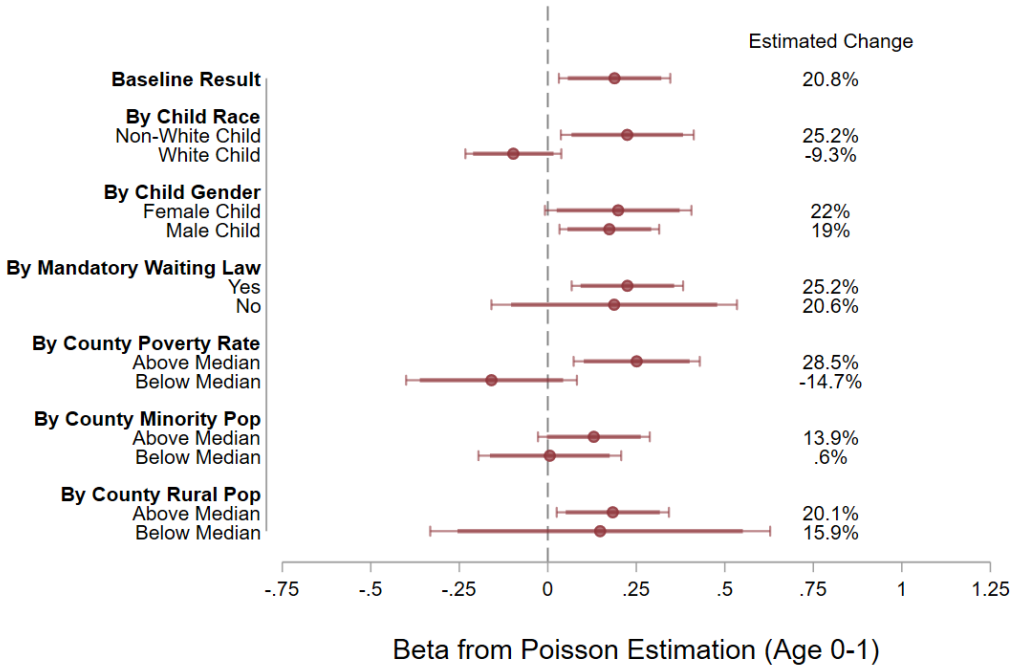


Figure 3. Heterogeneous Effects of Abortion Facility Distance on Child Maltreatment

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of child maltreatment for children stratified by child race, gender, or county characteristics. The primary outcome is the 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 (2) in Table 1. Specifically, we account for county fixed effects, year fixed effects, state-by-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, the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

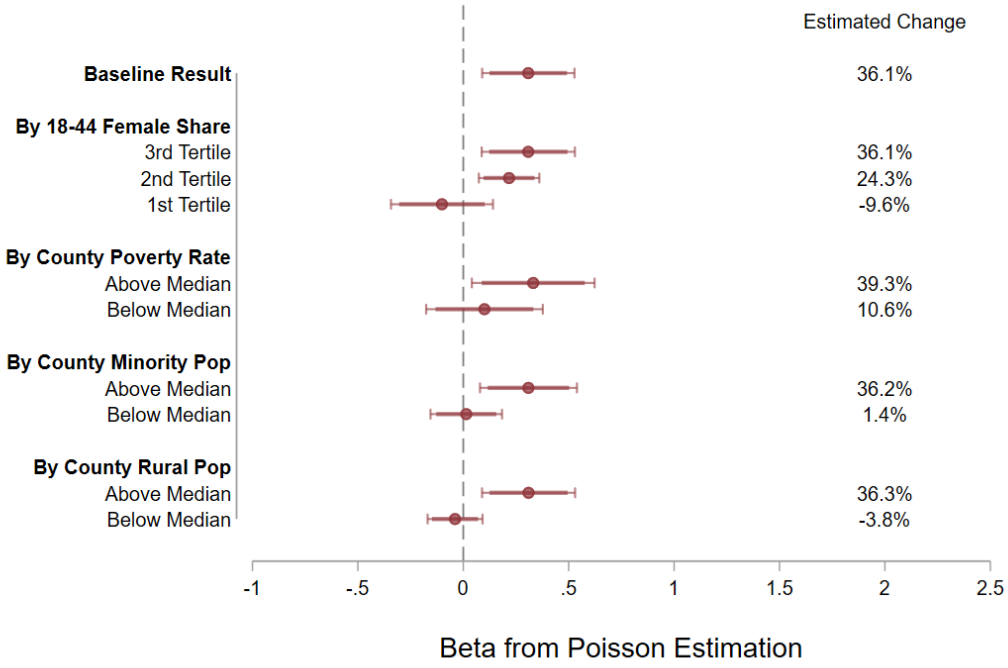


Figure 4. Heterogeneous Effects of Abortion Facility Distance on Evictions

Notes: This figure displays the impact of travel distance to the nearest abortion facility on the incidence of eviction filings stratified by county characteristics. The primary outcome is the number of eviction filings. Eviction filings is 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 number of households renting an property in each county. The analysis accounts for county fixed effects, year fixed effects, state-by-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, the number of abortion facilities in the destination county, and the average service population in the destination county (log-transformed). 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	0.870	0.870	0.870	0.870	0.870	0.870
County FE	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
County Demographics	√	√	√	√	√	√
State Policy Measures	√		√		√	
State × Year FE		√		√		√

Notes: This table presents the main findings on the impact of travel distance to the nearest abortion facility on 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 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, 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, the maximum food stamp benefit for a family of three, and the Earned Income Tax Credit (EITC) refund status. 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

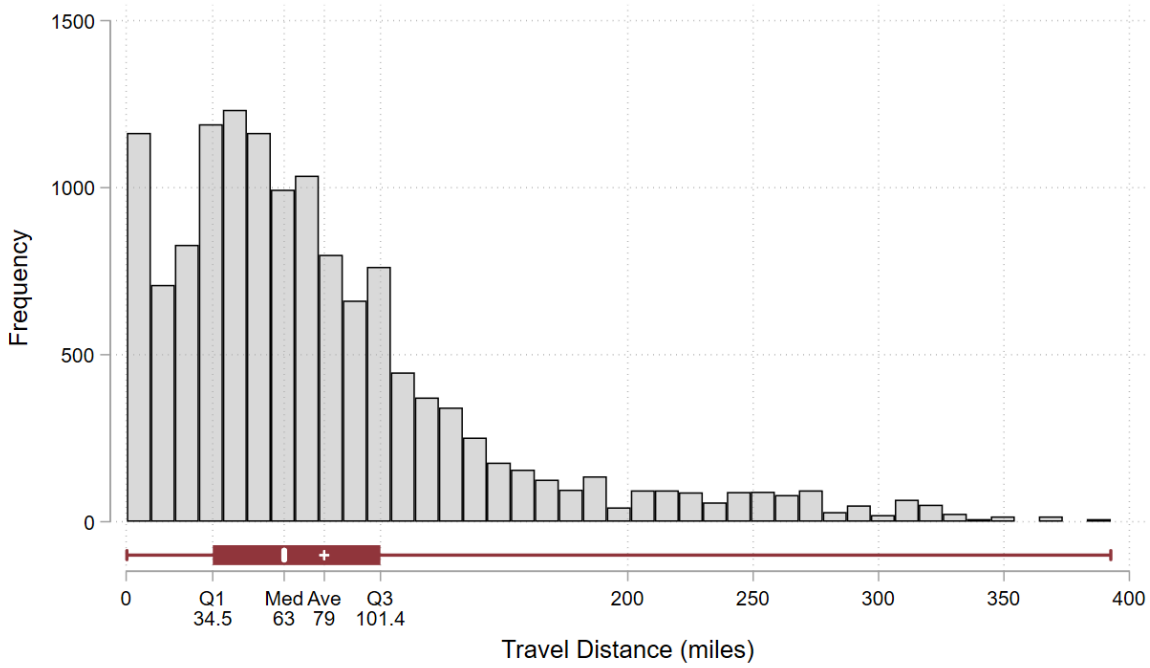


Figure A1. Histogram of Abortion Facility Distance

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.

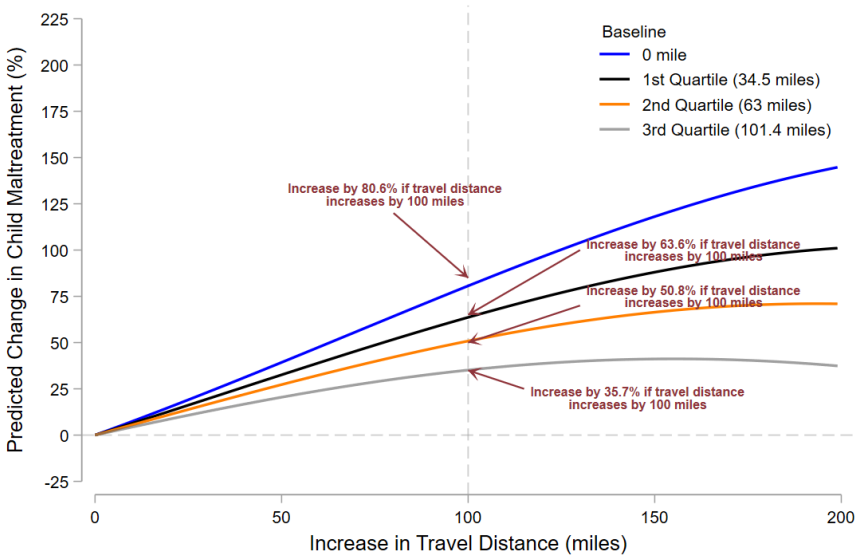


Figure A2. Nonlinear Effects of Abortion Facility Distance on Child Maltreatment

Notes: This figure displays the nonlinear effect of travel distance to nearest abortion facility on child maltreatment for children aged 1 or younger. Each curve shows the nonlinear effect given a baseline distance. Each curve is based on a Poisson estimation as specified in in column 4 in Table 1. We convert Poisson estimates to percentage changes using the transformation: $(exp(\hat{\beta}) - 1) \times 100\%$.

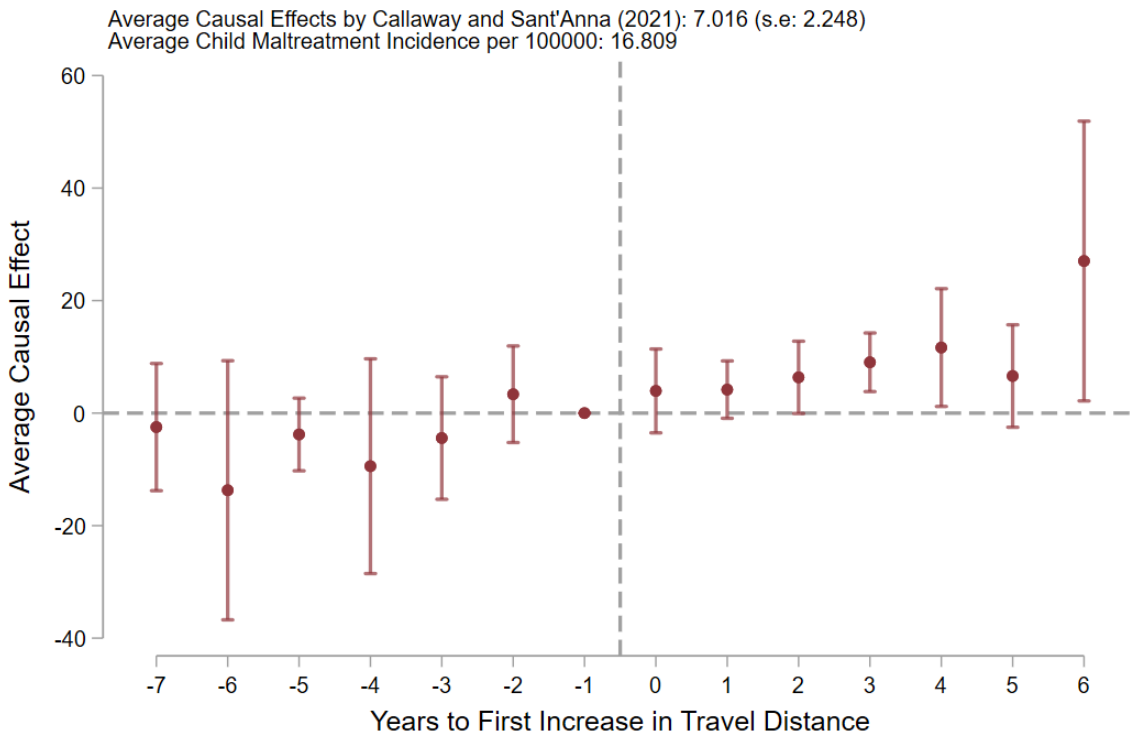


Figure A3. Effects of Abortion Facility Distance on Child Maltreatment: Event Study

Notes: This figure shows the event study analysis to compare pre-trends between counties before any change in travel distance using Callaway and Sant'Anna (2021) estimator. The primary outcome is the child maltreatment for children aged 1 or younger 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. 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.

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

Year	Agencies	Counties	States
(1)	(2)	(3)	(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 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	2.534	2.534	2.702	2.702	3.444	3.444
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 for different child age groups. 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, 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, the maximum food stamp benefit for a family of three, and the Earned Income Tax Credit (EITC) refund status. 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 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, 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, the maximum food stamp benefit for a family of three, and the Earned Income Tax Credit (EITC) refund status. 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 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. 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, 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, the maximum food stamp benefit for a family of three, and the Earned Income Tax Credit (EITC) refund status. Standard errors, clustered at the county level, are in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.