Crisis Response in Child Protection: Examining Foster Care Decisions During the Opioid Epidemic*

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Abstract

This paper examines how child protective services (CPS) responded to a significant increase in child maltreatment risk during the opioid epidemic. CPS plays a critical role in investigating maltreatment and placing at-risk children in foster care, an early childhood intervention with long-lasting impacts. Using the reformulation of OxyContin - one of the largest opioid supply disruptions in the United States - as a natural experiment, this study examines CPS responses to crises. By leveraging cross-state variation in pre-reformulation OxyContin misuse rates as a measure of differential exposure to the shock, I find that the reformulation led to an increase in maltreatment allegations from professional sources, including educational, medical, and social services personnel. However, while more children were exposed to maltreatment risk, CPS left more at-risk children in their homes. This is evidenced by a significant rise in false negatives, cases where children were not initially placed in foster care but were subsequently maltreated. These results reconcile prior studies documenting increased maltreatment allegations alongside stagnant or declining foster care placements during the opioid epidemic, suggesting that CPS responses have left at-risk children unprotected. This study highlights the need for strengthened CPS policies and resources to ensure timely and effective responses during crises, protecting vulnerable children from harm.

*The data used in this research were obtained from the National Data Archive on Child Abuse and Neglect and have been used in accordance with its Terms of Use Agreement License. The Administration on Children, Youth and Families, the Children's Bureau, the original dataset collection personnel, NDACAN, Duke University, Cornell University, and their agents or employees bear no responsibility for the analyses or interpretations presented here.

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1 Introduction

Child maltreatment has long-lasting impacts on victims' later life outcomes. Existing literature has documented that child maltreatment is associated with higher crime and incarceration rates, increased substance use, lower levels of employment, education, earnings, assets, and worse behavioral and mental health outcomes. (Spatz Widom, Marmorstein and Raskin White, 2006; Currie and Spatz Widom, 2010; Mersky and Topitzes, 2010; Currie and Tekin, 2012; Berger et al., 2016; Cicchetti and Handley, 2019). In 2022 alone, approximately 4.2 million child maltreatment allegations were reported in the United States (USDHHS, 2022). More than one-third of children undergo a maltreatment investigation by child protective services (CPS) before reaching the age of 18 (Kim et al., 2017).

How did CPS respond to the heightened risk of child maltreatment during a period of crisis? This paper examines foster care decisions of CPS in response to the increased child maltreatment risk induced by the reformulation of OxyContin amidst the opioid epidemic. I address this question in two steps. First, I analyze the extent to which the OxyContin reformulation increased maltreatment risk by examining changes in maltreatment allegations. Second, I assess foster care decisions by evaluating changes in false negatives — the cases where children were not placed in foster care but were subsequently maltreated.

CPS plays a critical role in investigating maltreatment and placing at-risk children in foster care, especially during crises that heighten the risk of maltreatment. When child maltreatment reports are made, CPS investigates the allegations and makes consequential decisions regarding the placement of children in foster care based on the risk of maltreatment if the child remains at home. Failure to remove at-risk children from home may result in their continued exposure to harmful environments, leading to further trauma or even fatalities. In addition, such failures are costly for the agency, as previously overlooked cases may be re-reported, necessitating the diversion of resources that could otherwise support new cases.

The reformulation of OxyContin was a nationwide supply-side drug policy aimed at curtailing the supply of OxyContin, the opioid painkiller that sparked the opioid epidemic (Alpert et al., 2022). In 2010, the Food and Drug Administration (FDA) approved a reformulated version of OxyContin with abuse-deterrent properties, designed to make it harder to crush or dissolve. The original version was then discontinued, significantly decreasing the supply of abusable prescription pain relievers. While intended to curb opioid misuse, the reformulation exacerbated the opioid epidemic, contributing to increased heroin and synthetic opioid use and opioid-related deaths (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019), increased rates of heroin-related arrests and homicides (Park, 2022; Tan, 2024). Parental substance abuse is strongly associated with higher risks of child maltreatment, making the reformulation a credible quasi-random shock to child maltreatment risk.

The identification strategy of this paper is akin to the Bartik approach (Bartik, 1991; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022), where it leverages variations in OxyContin misuse rates across states prior to its reformulation. Pre-reformulation OxyContin misuse rates measure differential exposure to the reformulation, as states with higher pre-reformulation OxyContin misuse rates experienced greater declines in OxyContin misuse rates following the intervention. Event study and difference-in-differences specifications are estimated to compare outcomes between states with greater exposure to the reformulation and those with lesser exposure.

I present two main sets of results. First, states with higher initial rates of OxyContin misuse experienced relatively larger increases in maltreatment allegations reported by professionals, including educational, medical, and social services personnel. Heterogeneity analyses suggest that the effects were more pronounced for allegations involving White children compared to allegations involving Black children. In light of the previous literature highlighting that White people were more severely impacted by the opioid epidemic than Black people, these heterogeneity analyses support the first empirical finding that the increase in maltreatment risk was driven by the opioid supply disruption.

Second, I find that while more children were exposed to maltreatment risk following the opioid supply disruption, CPS left more at-risk children in their homes. This is empirically supported by a significant rise in the rate of false negatives — cases where children were not initially placed in foster care but were subsequently maltreated — in states with high initial OxyContin misuse rates compared to states with low initial misuse rates. These results suggest that serious maltreatment cases prompted by the opioid epidemic have been neglected by CPS. In addition to these main results, I show that this misalignment between an increase in maltreatment risk and CPS placement decisions was not primarily driven by the shortage of foster homes or reliance on post-response services.

This paper makes several contributions to the literature. First, it adds to the growing body of economic literature on child welfare by examining the responsiveness of CPS foster care placement policies in the face of heightened maltreatment risk. While prior research has primarily focused on the causal effects of foster care placements on children's long-term outcomes (Doyle Jr, 2007, 2008; Bald et al., 2022*a*; Baron and Gross, 2022; Gross and Baron, 2022), little attention has been paid to how CPS has responded to nationwide shocks that heightened maltreatment risk. This gap in the literature is policy-relevant because large-scale shocks to child maltreatment risk are not uncommon. They can occur due to drug epidemics (Evans, Lieber and Power, 2019), economic recessions (Brooks-Gunn, Schneider and Waldfogel, 2013), and even rising temperatures induced by climate change (Evans, Gazze and Schaller, 2023). This study highlights the need for adaptable child welfare policies to protect children during crises.

Second, this paper reconciles two economic studies that have documented seemingly contradictory findings regarding the impact of the opioid epidemic on child welfare. Evans, Harris and Kessler (2022) documented an increase in maltreatment allegations following the reformulation of OxyContin and the implementation of mandatory Prescription Drug Monitoring Programs (PDMPs), whereas Gihleb, Giuntella and Zhang (2022) documented stagnant or declining foster care placements following the introduction of PDMPs. The absence of a unifying framework suggests a disagreement between these findings. By introducing the framework of prediction mistakes, I show that these findings are not contradictory, but suggest a misalignment between increased maltreatment risk and CPS placement decisions during this period of heightened opioid-related family instability.

Third, this paper complements the literature examining supply-side drug policies. The economic literature has studied various policies aimed at curtailing the supply of abusable drugs. These policies include Prescription Drug Monitoring Programs (Buchmueller and Carey, 2018; Grecu, Dave and Saffer, 2019; Gihleb, Giuntella and Zhang, 2022), crackdowns on doctors and pain clinic suppliers (Dobkin and Nicosia, 2009; Meinhofer, 2016; Soliman, 2023), triplicate prescription programs (Sigler et al., 1984; Weintraub et al., 1991; Hartzema et al., 1992; Simoni-Wastila et al., 2004), implementation of over-the-counter regulations (Dobkin, Nicosia and Weinberg, 2014), and reformulation of OxyContin (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019; Evans, Harris and Kessler, 2022). While previous studies typically examine the impact of each supply-side drug policy in isolation, this paper explores a unique setting where an initial policy is followed by a government response, which may either mitigate or amplify the effects of the initial policy. This highlights the concept of policy complementarities, where the benefits of policies can be reinforced, or the negative consequences of initial policies can be mitigated through the synergistic interaction of multiple policies (Coe and Snower, 1997; Orszag, 1998; Chang, Kaltani and Loayza, 2009).

Lastly, this paper expands upon existing literature that examines the consequences of the opioid epidemic. Studies have documented that opioid epidemic has led to higher health care costs (White et al., 2005; Leslie et al., 2019), lower labor force participation rates and higher unemployment rates (Harris et al., 2020), higher crime rates (Sim, 2023), and more suicides (Borgschulte, Corredor-Waldron and Marshall, 2018). These findings suggest that vulnerable populations have been disproportionately affected by the opioid epidemic, further widening socioeconomic inequality. By examining the impact of the opioid epidemic on children, this paper demonstrates that the epidemic can have intergenerational consequences on mobility and inequality.

2 Background

2.A Parental Substance Abuse and Child Maltreatment

Existing literature has documented a strong association between parental substance abuse and child maltreatment. Drug addiction disrupts the neural circuits responsible for reward, stress reactivity, and regulation, which significantly impairs parenting abilities. This disruption lowers the salience of infant signals and heightens the stress associated with caregiving (Rutherford and Mayes, 2017). Beyond impairing the capacity to care for children, substance abuse is also linked to outcomes that expose children to unsafe and violent environments (Walsh, MacMillan and Jamieson, 2003; White and Widom, 2008; Conners-Burrow, Johnson and Whiteside-Mansell, 2009; Raitasalo and Holmila, 2017). For example, seeking illicit drugs often necessitates engaging in criminal activities, further increasing the risk to children's safety and well-being (Powis, 2000).

Since 2005, parental substance abuse has consistently been the second most prevalent risk factor associated with child removal from home, following domestic violence, and accounting for 20% to 36% of all cases. In 2022, 23.8% of child maltreatment victims had the drug abuse caregiver risk factor (Children's Bureau, 2022). Moreover, nearly half of mothers in maltreatment referrals, even without substance-related allegations, have a history of substance abuse, with opioids being the most common substance (Font and Goldstein, 2024). Parental substance abuse as a primary driver of child maltreatment suggests that the risk of maltreatment has risen significantly since the opioid epidemic, the worst drug overdose crisis in U.S. history.

2.B Foster Care in the United States

By the age of 18, as many as 6% of all children in the United States, including 16% of Native American children and 12% of Black children, will have experienced foster care at some point in their lives (Wildeman and Emanuel, 2014). When child maltreatment is suspected, any individual, including certain professionals who are mandated to report by law, can make a report by calling a hotline. These reports are then screened to determine if they warrant further investigation, with some being routed to local CPS offices. Once a report reaches CPS, investigators assess the evidence. If sufficient evidence supports the maltreatment allegation, the case is substantiated.

For substantiated cases, CPS has the authority to intervene based on the severity of the situation. The most significant intervention is the removal of children from their homes and placement into foster care. In these cases, children are placed in foster homes, where they reside while efforts are made to address the issues within their families. Parents are typically required to comply with a reunification plan, which may involve participation in rehabilitation or detox programs, especially when parental substance abuse is the cause of the child's removal. The ultimate goal of CPS is to reunify families whenever it is safe and feasible, though this process often involves navigating complex and challenging dynamics between child welfare, parental rights, and the best interests of the child.

2.C Opioid Epidemic

Since the 1990s, the United States has seen a sharp increase in fatalities caused by drug overdoses. From 1999 to 2022, nearly 727,000 people died from an opioid overdose (CDC, 2023). The opioid overdose death rate increased significantly from 2.9 per 100,000 people in 1999 to 32.4 per 100,000 in 2021 (NCHS, 2023). The unprecedented surge in deaths from opioid overdoses has led the Centers for Disease Control and Prevention (CDC) to declare this the most severe drug overdose crisis in U.S. history (Kolodny et al., 2015).

Starting in the 1990s, changing perceptions of the opioids and updated treatment protocols led physicians to take a more aggressive approach in managing pain with opioids. (Jones et al., 2018). The American Pain Society initiated a significant campaign to recognize pain as the fifth vital sign in 1995. Consequently, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) updated its guidelines in 2001 to mandate that physicians evaluate pain together with other vital signs during patient consultations (Phillips, 2000).

Moreover, Purdue Pharma introduced OxyContin in 1996, a prescription opioid painkiller that rapidly emerged as one of the top substances misused in the United States with global sales reaching $35 billion (Cicero, Inciardi and Muñoz, 2005). OxyContin, which is the brand name for the opioid oxycodone hydrochloride, is a pain reliever with a controlled-release mechanism, intended to be taken orally without breaking or crushing. It was intended to be prescribed for the alleviation of moderate to severe pain stemming from conditions such as injuries, bursitis, neuralgia, arthritis, and cancer. Nevertheless, individuals could unlock the high dosage of oxycodone instantly by dissolving or crushing the pill, resulting in an immediate euphoric effect. Because of its significant potential for abuse, it is categorized as a Schedule II controlled substance. Recent economic studies demonstrated that the introduction and marketing of OxyContin account for a significant portion of overdose deaths, declines in the quality of life, and deteriorating children's health over the past two decades, thereby suggesting it as a primary cause of the opioid epidemic (Alpert et al., 2022; Arteaga and Barone, 2022).

2.D Reformulation of OxyContin and Child Welfare

In response to the escalating misuse of OxyContin, Purdue Pharma released an abuse-deterrent formulation of the drug, which was approved by the Food and Drug Administration (FDA) in 2010. The reformulated OxyContin was designed to be more difficult to dissolve or crush, thereby making it more challenging to abuse through ingestion, inhalation, or injection for immediate euphoric effects. Following the reformulation, there was a swift decrease in both the misuse of OxyContin and the distribution of oxycodone. Between 2010 and 2014, the national rate of self-reported OxyContin misuse dropped approximately by 40 percent, and for the first time, the overall legal distribution of oxycodone, as tracked by the DEA, saw a decline after the reformulation, ending a consistent rise that had been ongoing since 2000 (Alpert, Powell and Pacula, 2018).

However, studies have documented unintended consequences of the OxyContin reformulation. For example, several medical studies have found that the use of heroin and synthetic opioid, which are more potent than OxyContin, surged immediately after the reformulation (Coplan et al., 2013; Cicero and Ellis, 2015; Larochelle et al., 2015). Moreover, economic studies identified a causal relationship between the OxyContin reformulation and an increase in opioid overdose deaths (Powell and Pacula, 2021), deaths related to heroin and synthetic opioids (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019), cases of Hepatitis and HIV (Beheshti, 2019), and homicides (Park, 2022; Tan, 2024).

These results suggest that the reformulation of OxyContin likely increased children's exposure to maltreatment risk at home through multiple channels. First, an increase in the overall opioid overdose deaths indicates that more parents were adversely affected. Second, the neurobiological effects of heroin on parents would have heightened the risk. Compared to prescription opioids, heroin is more addictive (Health-Americas, 2023) and associated with more severe withdrawal symptoms (Monico and Mitchell, 2018), which likely impaired the parenting behaviors of users, increasing children's exposure to maltreatment risk. Third, crimes associated with obtaining heroin may have further elevated risks to children. Unlike prescription opioids, heroin is an illicit drug and cannot be legally purchased, often leading to high-risk criminal behaviors to obtain the substance. Mallatt (2022) and Powell and Pacula (2021) documented an increase in heroin-related arrests following the reformulation, while Park (2022) and Tan (2024) noted a rise in homicide rates, suggesting that heightened illicit market activities led to more crimes.

3 Conceptual Framework

In this section, I formally define false negatives based on the foster care decision made by CPS, which operates under clear policy guidelines. The primary justification for placing a child in foster care is the potential risk of maltreatment if the child is left at home.[1] Each child has a potential for subsequent maltreatment $Y_i^* \in \{0,1\}$ where $Y_i^* = 1$ indicates that a child would be maltreated if left at home following the CPS investigation. Let $D_i \in \{0,1\}$ denote the placement decision for child i where $D_i = 1$ indicates that a child is placed in foster care. Then false negative for child i is defined as follows:

$$FN_i = \mathbb{1}(Y_i^* = 1, D_i = 0)$$

The false negative rate can be expressed as follows:

$$\begin{aligned}\mathbb{P}(Y_i^* = 1, D_i = 0) &= \mathbb{P}(Y_i^* = 1) \times \mathbb{P}(D_i = 0 | Y_i^* = 1) \\ &= \underbrace{\mathbb{P}(Y_i^* = 1)}_{\text{Prevalence of at-risk children}} \times (1 - \underbrace{\mathbb{P}(D_i = 1 | Y_i^* = 1)}_{\text{Placement rate of at-risk children}})\end{aligned}$$

where $\mathbb{P}(Y_i^* = 1)$ represents the fraction of children at risk of subsequent maltreatment and $\mathbb{P}(D_i = 1 | Y_i^* = 1)$ represents the placement rate for children with subsequent maltreatment potential. Any shock that affects the risk of maltreatment changes $\mathbb{P}(Y_i^* = 1)$. $\mathbb{P}(D_i = 1 | Y_i^* = 1)$ captures CPS's placement tendencies for at-risk children. An increase in the false negative rates, in response to a shock that raises the fraction of children at risk of subsequent maltreatment, suggests that CPS did not sufficiently increase the placement rate for at-risk children to offset the rise in subsequent maltreatment potentials.

The empirical challenge in measuring false negatives lies in the fact that Y_i^* is a latent variable. I use re-investigations initiated through the reports from professional reporters as a proxy for subsequent maltreatment. Details about the classification of professional

[1] CPS policy manuals in many states explicitly mandate this as a core objective (MDHHS, 2020; NCDHHS, 2024).

reporters are explained in Section 4. Re-investigations within six months of the initial investigation where the child was left at home are widely used as a proxy for subsequent maltreatment in both academic research and policy evaluation of child welfare systems (Antle et al., 2009; Putnam-Hornstein et al., 2015; Putnam-Hornstein, Prindle and Hammond, 2021; Baron et al., 2024*a*,*b*). Although this measure serves as an imperfect proxy for false negatives, re-investigations involve considerable interactions with authorities that entail a report to CPS and screening procedures in the central hotline center. Nonetheless, I show the robustness of the main results to alternative measures that involve decisions of CPS, including substantiation and foster care placement following the allegation by professionals.

4 Data

I use several data sources for the analysis. The primary data for child welfare are collected from the National Child Abuse and Neglect Data System (NCANDS) and the Adoption and Foster Care Analysis and Reporting System (AFCARS). NCANDS is a federally funded initiative that gathers yearly data on child abuse and neglect cases reported to CPS across the United States. Reporting to NCANDS by states is voluntary, yet the majority of states and the District of Columbia provide data during the timeframe of the analysis in this paper.[2] AFCARS, a data collection system required by federal mandate, gathers detailed information on all children protected under Title IV-B/E of the Social Security Act (Section 427). This database compiles data on every child in foster care and those adopted through the jurisdiction of state child welfare agencies. Since 1998, it has been compulsory for states to participate in this program. I use NCANDS Child Files 2003-2020 and AFCARS Foster Care Files 2004-2016 for the analysis.[3] For the analysis of false negatives, I exclude states where the successful matching rate between Child Files from t to $t+1$ is below 90% for more than two years within the period $t \in \{2004, \cdots 2015\}$.[4] Additionally, I exclude states that do not report foster care placements. These criteria yield a sample of 39 states for the analysis of false negatives.

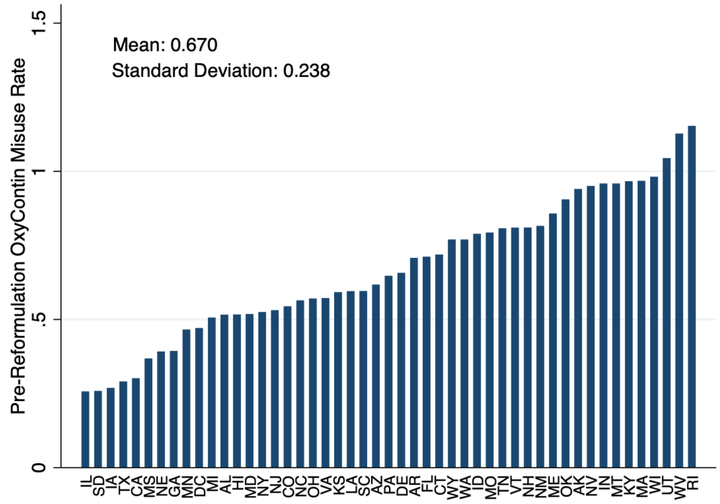
I utilize the measures for nonmedical OxyContin use before its reformulation, covering

[2]In the NCANDS data, Oregon and North Dakota were excluded because they did not report during the sample period.

[3]The analysis period of this paper covers 2004-2016. I use the report year rather than the submission year of each allegation because the former represents when the agency was notified of the case. Since report years and submission years do not always align, I include some waves of the NCANDS Child Files outside of the analysis period to minimize the loss of reported allegations in the sample.

[4]The proportion of successful links of Child IDs across annual child files is based on the child's date of birth and sex. These rates are reported in the file "Linking the NCANDS Child File Year to Year" provided by NDACAN.

Figure 1: Pre-reformulation Rate of OxyContin Misuse



Notes. This figure illustrates the rate of nonmedical use of OxyContin in each state between 2004 and 2009. The mean and the standard error of the misuse rate is 0.670 and 0.238, respectively.

the period from 2004 to 2009. I retrieve these measures from Alpert, Powell and Pacula (2018), which are based on data from the National Survey on Drug Use and Health (NSDUH).[5] The NSDUH is a household survey that represents the national population and includes individuals aged 12 and above. It is the largest annual survey that collects data on substance use in the U.S. and specifically mentions OxyContin, distinguishing its nonmedical use. The pre-reformulation exposure to nonmedical OxyContin use is defined as the population-weighted rate in each state, combining survey data from 2004-2005 to 2008-2009. Alpert, Powell and Pacula (2018) showed that state-level OxyContin misuse rates from NSDUH align with both the legal supply data from the Automation of Reports and Consolidated Orders System (ARCOS) and opioid prescription data from the geocoded Medical Expenditure Panel Survey (MEPS). The empirical strategy is based on the idea that the reformulation of OxyContin had a greater impact in states with higher rates of pre-reformulation nonmedical OxyContin use, compared to states with lower misuse rates. Figure 1 shows that there exists significant variation in the pre-reformulation rate of OxyContin misuse across states.

The outcomes of interest are maltreatment allegations reported by professionals per 1,000

[5] Evans, Harris and Kessler (2022) use data on prescription opioids from CDC as the primary measure for the exposure to prescription opioids. While these measures provide county-level variation, they do not distinguish the use of OxyContin from other drugs, nor do they specify nonmedical use of the drug.

children and false negatives per 1,000 children and per 1,000 allegations. Professionals include social services, medical, mental health, legal, education personnel, and child daycare providers. I focus primarily on professional reports because they are likely to provide less biased estimates of underlying maltreatment risk. The reformulation of OxyContin was a nationwide intervention that influenced not only potential perpetrators but also potential reporters of maltreatment. This implies that reporters' abilities to identify and report maltreatment, as well as the consistency of reporting standards, may have been compromised by the intervention.

However, professionals are less likely to be affected in this way compared to non-professionals — primarily neighbors, friends, and relatives — for two reasons. First, studies show that professionals, as classified above, had the lowest rates of substance use disorders (SUD) from 2008 to 2012 (Bush and Lipari, 2016). Furthermore, these occupations demonstrated substantially lower rates of opioid-related overdose deaths—ranging from 4 to 15.4 deaths per 100,000 workers, compared to the occupational average of 25.1 during 2011-2015 in Massachusetts (Hawkins et al., 2019). The lower levels of substance dependence, particularly regarding opioids, suggest that professionals' abilities to report maltreatment were likely less impaired following OxyContin's reformulation, relative to non-professionals. Second, professionals are mandated reporters in most states and are provided with training and resources to support their ability to identify and report child maltreatment. This mandate likely enabled them to maintain greater consistency in reporting standards during periods of crisis compared to non-professionals.

Table 1 presents summary statistics for the pre-reformulation period (2004-09), categorized separately for states with a pre-reformulation OxyContin misuse rate below and equal to or above the sample mean of 0.657. The third column displays the p-values from tests for the equality of means. Compared to the low-exposure states, high-exposure states have higher rates of false negatives and populations that are more White, less Black, and older.

Table 1: Summary Statistics

Variable	Low-exposure states	High-exposure states	p-value	Data source
Allegations per 1,000 Children	20.908	28.263	0.108	NCANDS
False Negatives per 1,000 Children	2.060	2.640	0.008	NCANDS
False Negatives per 1,000 Allegations	52.890	59.178	0.033	NCANDS
OxyContin misuse rate	0.447	0.842	0.000	Alpert et al.
Percent White	76.911	84.372	0.000	Census
Percent Black	14.526	9.582	0.054	Census
Percent Hispanic	17.133	10.671	0.201	Census
Percent female	50.876	50.826	0.803	Census
Percent age 0 to 19	27.900	26.720	0.094	Census
Percent age 20 to 24	7.065	6.918	0.344	Census
Percent age 25 to 34	13.471	12.763	0.027	Census
Percent age 35 to 44	14.417	14.025	0.032	Census
Percent age 45 to 54	14.427	14.632	0.383	Census
Percent age 55 to 64	10.598	11.289	0.009	Census
Percent over age 64	12.101	13.652	0.068	Census
Unemployment rate	6.014	5.437	0.062	BLS
Labor force participation rate	66.077	65.603	0.640	BLS

Notes. This table reports means for the pre-reformulation period from 2004 to 2009. Low-exposure states are defined as the 25 states where the rate of OxyContin misuse prior to the reformulation was below the median rate of 0.657. High-exposure states include all other states. Allegations refer to reports made by professionals. The third column reports the p-values for the equality of means tests.

5 Empirical Strategy

To examine the causal effects of the OxyContin reformulation, I estimate event study and difference-in-differences regressions, leveraging the variation in states' pre-reformulation exposure to nonmedical use of OxyContin. This design is akin to the Bartik approach (Bartik, 1991; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022) in that the pre-reformulation OxyContin misuse rate represents states' differential exposure to the reformulation of OxyContin. The local "shares" are states' pre-reformulation OxyContin misuse rates and the "common shock" is the OxyContin reformulation. For the event study, I estimate the following equation:

$$y_{st} = \sum_{k=2004}^{2016} \beta_k \mathbb{1}[t = k] \times \text{Exp}_s + \alpha_s + \gamma_t + X'_{st}\lambda + \epsilon_{st} \tag{1}$$

where y_{st} denotes the outcome in state s and year t, α_s denotes state fixed effects, and γ_t denotes year fixed effects. Exp_s denotes a standardized pre-reformulation rate of nonmedical OxyContin use as described above. X_{st} denotes a vector of state- and time-varying covariates including the percent White, percent Black, percent Hispanic, percent female, percent of the state population in six age groups (0-19, 20-24, 25-34, 35-44, 45-54, 55-64), unemployment rate, labor force participation rate and state- and time-varying policy indicators for a must-access Prescription Drug Monitoring Program, medical marijuana law and Medicaid expansion. I normalize the coefficient for year 2010 to zero and cluster standard errors at the state level. The variables of interest are β_t terms which identify how the outcomes in state s and year t would have been different had its pre-reformulation OxyContin misuse rate been one standard deviation higher.

I also estimate a DID specification to estimate the short-run and medium-run effects of OxyContin's reformulation. I estimate the following equation:

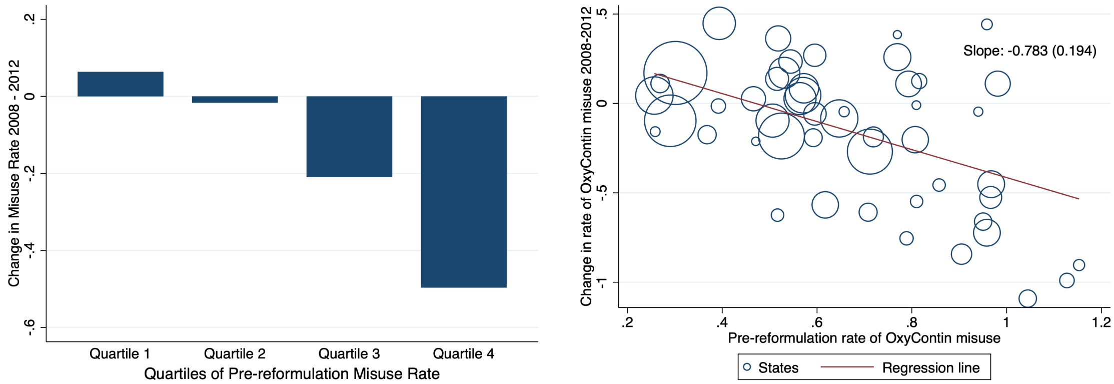
$$\begin{aligned} y_{st} = {} & \beta_1 \times \text{Pre}_t \times \text{Exp}_s + \beta_2 \times \text{SRpost}_t \times \text{Exp}_s + \beta_3 \times \text{MRpost}_t \times \text{Exp}_s \\ & + \alpha_s + \gamma_t + X_{st}'\lambda + \epsilon_{st} \end{aligned} \tag{2}$$

where Pre_t takes a value of 1 for pre-reformulation years from 2004 to 2009. SRpost_t takes a value of 1 for years 2011 to 2013 and MRpost_t takes a value of 1 for years 2014 to 2016. y_{st} and X_{st} are defined as above. Standard errors are clustered at the state level. The variables of interest are β_1, β_2 and β_3 terms which identify how the outcomes in state s would have been different in the pre-reformulation period, short-run and medium rum following the reformulation had its pre-reformlation OxyContin misuse rate been one standard deviation higher.

The identification strategy builds upon two assumptions: pre-reformulation OxyContin misuse rate is (1) correlated with the exposure to the reformulation and (2) is not correlated with factors that could affect the differential trends in maltreatment allegations and false negatives after the reformulation, in the absence of the reformulation. Figure 2 presents the "first-stage" results, demonstrating the association between pre-reformulation OxyContin misuse rates and the changes in misuse rates following the reformulation. Both the plot illustrating changes in misuse rates by quartile of pre-reformulation rates and the weighted least squares regression of the change in misuse rates on pre-reformulation rates suggest that states with higher pre-reformulation OxyContin misuse rates experienced larger declines in misuse rates following the reformulation. Regression results with covariates are reported in Table A1. These results are consistent with the findings of Alpert, Powell and Pacula (2018), which indicate that the reformulation of OxyContin had a stronger impact on states that were more exposed to nonmedical use of OxyContin prior to the reformulation.

The second assumption requires that the "shares" (or pre-reformulation OxyContin

Figure 2: Pre-reformulation Rate of OxyContin Misuse and Change between 2008-2012



(a) Change Rates by Quartile

(b) Weighted Least Squares

Notes. This figure plots the relationship between pre-reformulation rate of OxyContin misuse and change between 2008 and 2012. Figure (a) plots the changes in the rate of OxyContin misuse from 2008 to 2012 against the quartiles of pre-reformulation rate of OxyContin misuse. Figure (b) plots the weighted least squares (WLS) fitted line regressing the change in the rate of OxyContin misuse from 2008 to 2012 on the pre-reformulation rate of OxyContin misuse, using state population in 2008 as weights. Standard errors are clustered at the state level.

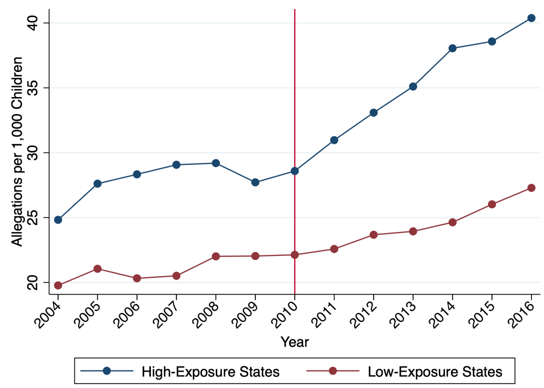
misuse rates) are exogenous to *changes*, as opposed to *levels* of the outcome variables (Goldsmith-Pinkham, Sorkin and Swift, 2020). Empirically, one can assess the plausibility of this assumption by performing pretrends tests as suggested in the recent literature on the exposure designs (Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022). In the next section, I show that pre-reformulation estimates of the outcomes are indistinguishable from zero in the event study and difference-in-differences results.

6 Results

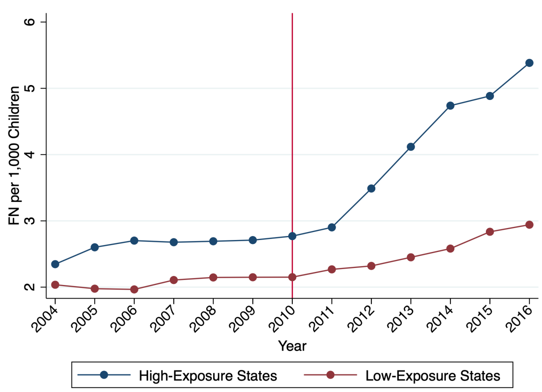
6.A Preliminary Evidence

Before presenting the main even study and difference-in-differences results, I present differential trends in the outcomes between states with above-median (high-exposure states) and below-median (low-exposure states) initial OxyContin misuse rates as preliminary evidence. Figure 3 shows trends in maltreatment allegations reported by professionals per 1,000 children and false negatives per 1,000 allegations and children from 2004 to 2016 for high- and low-exposure states. Allegations have increased in both high- and low-exposure states, with a steeper rise observed in the high-exposure states. Between 2010 and 2016, allegations increased by 41% in high-exposure states, compared to a 23% increase in low-exposure states.

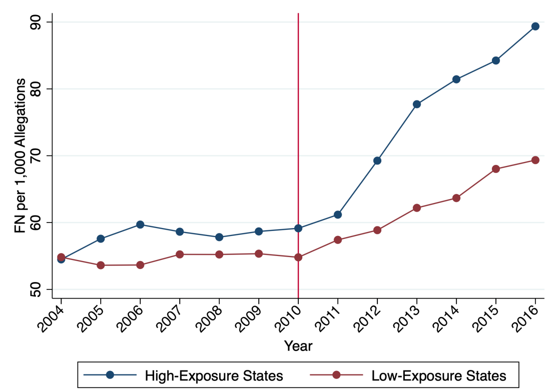
Figure 3: Trends in Maltreatment Allegations and False Nagatives



(a) Allegations per 1,000 Children



(b) False Negatives per 1,000 Children



(c) False Negatives per 1,000 Allegations

Notes. This figure illustrates the trends in maltreatment allegations reported by professionals per 1,000 children and false negatives per 1,000 children and allegations from 2004 to 2016 separately for states with a pre-reformulation OxyContin misuse rate above or below and equal to the sample mean of 0.657.

Before the reformulation, the trends in false negatives were nearly identical between the two groups. However, post-reformulation, false negatives surged in high-exposure states, while in low-exposure states, they continued to increase at a rate similar to that observed before the reformulation. Between 2010 and 2016, false negatives per 1,000 children nearly doubled in high-exposure states, while rising by just 37% in low-exposure states. False negatives per 1,000 allegations increased by approximately 51% in high-exposure states, compared to only a 27% increase in low-exposure states.

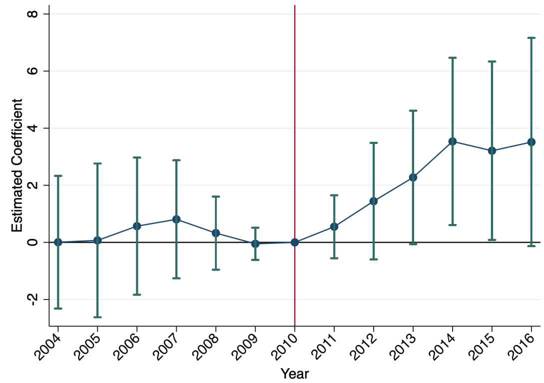
6.B Main Results

Figure 4a and Table 2 show the event study and difference-in-differences results for the allegations reported by professionals per 1,000 children, and false negatives per 1,000 allegations and children. The allegations reported by professionals increased following the reformulation. A one standard deviation increase in the initial OxyContin misuse rate yields about a 6% rise in allegations during the first three years after the reformulation, followed by a 14% increase in the subsequent three years. Figure A4 and Table A5 report the results for allegations made by non-professionals. The magnitude of the effects suggests that allegations by non-professionals increased at a rate comparable to those reported by professionals, though with larger standard errors. Notably, physical abuse allegations showed the highest rates of increase, with these estimates achieving statistical significance.

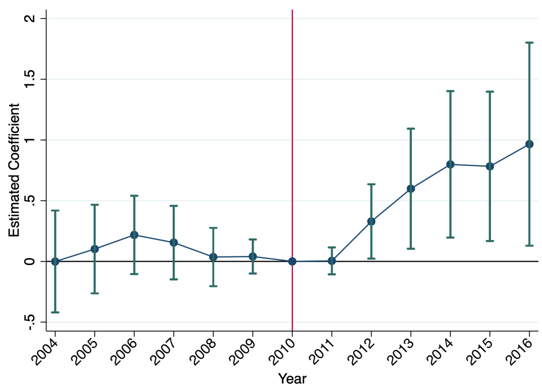
The event study and difference-in-differences results indicate that false negatives increased following the reformulation. A one standard deviation increase in the initial OxyContin misuse rate yields about 13% and 34% increase in false negatives per 1,000 children in the short- and medium-run, respectively. When considering false negatives per 1,000 allegations, this translates to an increase of approximately 5% in the short run and 10% in the medium run. Figures A9, A8 and Tables A9, A8 present the results based on alternative measures of false negatives, where subsequent substantiation and foster care placement within six months following reports from professionals are used. While I prefer using subsequent allegations as a measure of false negatives — since other measures may be endogenously determined, as re-referrals are often assigned to the initial investigators (Baron et al., 2024*a*) — the increase in false negatives following the reformulation is robust across different measures, although the magnitudes and statistical significance vary.

These findings provide insights into how CPS responded to the increased maltreatment risk during the opioid epidemic. Despite the rise in maltreatment allegations, a greater number of at-risk children were left in their homes, continuing to face exposure to maltreatment risk. The robustness of the increase in false negative rates, as measured by CPS decisions including subsequent substantiation and foster care placement, suggests that these results do not merely reflect discrepancies between reporters and CPS. Instead, they highlight potential challenges in accurately identifying and effectively intervening in high-risk situations.

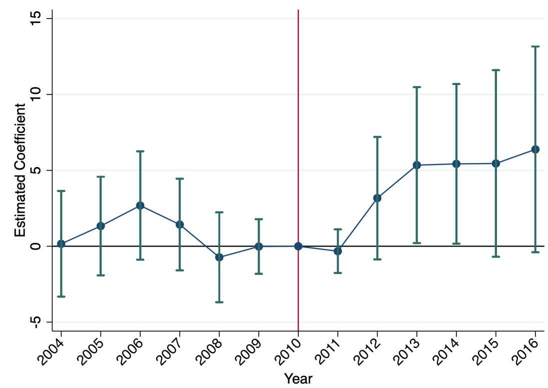
Figure 4: Event Study Results for Allegations and False Negatives



(a) Allegations per 1,000 Children



(b) FN per 1,000 Children



(c) FN per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 1,000 children reported by professionals and false negatives per 1,000 children and allegations. Regressions are weighted by child population.

6.C Heterogeneity Analysis

Table A2 presents the percentage breakdown of allegations by maltreatment type, child characteristics, and report sources, separately for all allegations and for those made by professionals during the sample period from 2004 to 2016. Neglect is the most common type of maltreatment, comprising 60.4% of all allegations, followed by physical abuse, which accounts for 21.8%. Among professional reports, neglect and physical abuse remain the most frequent types of maltreatment, making up approximately 77% of these allegations. Education, legal, social services, and medical personnel are the most common sources of

Table 2: Difference-in-Differences Results for Allegations and False Negatives

	(1) Professional Allegations	(2) False Negatives per 1,000 Children	(3) False Negatives per 1,000 Allegations
Pre-reformulation	0.299	0.086	0.686
	(0.816)	(0.119)	(1.195)
Short-run	1.394*	0.301**	2.651
	(0.825)	(0.129)	(1.597)
	[5.8%]	[12.8%]	[4.7%]
Medium-run	3.327**	0.808**	5.397*
	(1.548)	(0.321)	(2.832)
	[13.9%]	[34.4%]	[9.6%]
Mean (2010)	23.976	2.351	56.377
R-squared	0.887	0.767	0.816
Observations	634	506	506
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are maltreatment allegations per 1,000 children reported by professionals and false negatives per 1,000 children and allegations. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

reports, accounting for 51% of all allegations. Among reports made by professionals, these groups represent 91% of the total.

Table A4 and Figure A3 present the results for allegations by child characteristics: race, gender, and age. The results indicate that the effects of the reformulation were heterogeneous across racial groups, with maltreatment allegations for White children increasing at a rate approximately 2.3 times higher than those for Black children. The p-value associated with the two rates being equal is 0.065. These findings are consistent with the existing literature, which documents that the opioid epidemic has disproportionately impacted White populations compared to Black populations. Specifically, White individuals are twice as likely as non-White minorities to use prescription opioid painkillers for non-medical purposes (Netherland and Hansen, 2016).

This racial disparity in opioid misuse is largely attributed to non-White minorities receiving inadequate pain management in various healthcare settings (Burgess et al., 2006; Sabin et al., 2009; Santoro and Santoro, 2018; Nicolette Harris, Long et al., 2021). Consequently, White people, who are more frequently prescribed opioid pain relievers, were likely more affected by the disruption in opioid supply following the reformulation. This increased exposure to opioids among White people may have led to a higher rate of associated negative outcomes, including increased rates of child maltreatment allegations.

Table A3, Figure A1 and Figure A2 present the results for allegations categorized by maltreatment type and report source. Neglect and physical abuse, which together account for 82% of all allegations and 77% of professional allegations, both increased following the reformulation. In terms of report sources, the increase in allegations was primarily driven by education, social services, and medical personnel. Table A7, Table A6, Figure A5 and Figure A6 report the results for false negatives by maltreatment types and child characteristics. These results show that false negatives increased across all types of cases and demographics of children.

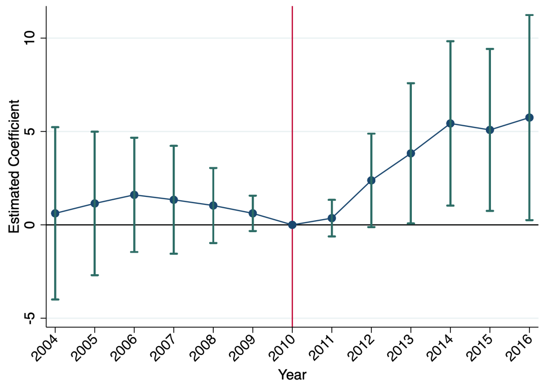
6.D Robustness Checks

Figures A8 and A9, along with Tables A8 and A9, present the event study and difference-in-differences results for alternative measures of false negatives. These measures are based on CPS decisions following allegations made by professionals, specifically focusing on substantiation and foster care placements within six months of an initial investigation that resulted in the child being left at home. The robustness of these results suggests that increases in allegations and false negatives are not merely a result of disagreements between reporters and CPS regarding the maltreatment potential of children but rather reflect a misalignment between rising underlying risks and CPS placement decisions.

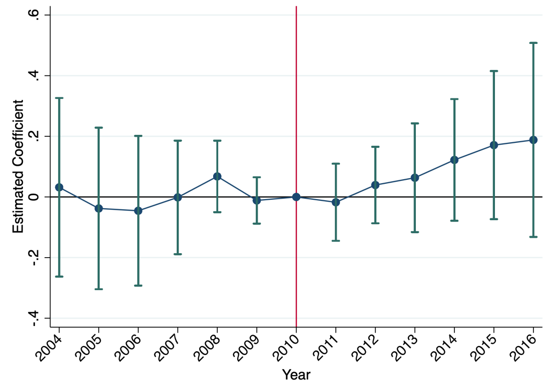
Alternative empirical specifications have been estimated for robustness checks. Figure A11 and Table A10 present results based on a binary treatment, where the exposure measure is defined as an indicator taking the value of one if the state's pre-reformulation OxyContin misuse rate is above the median. Figure A12 and Table A11 display results where the dependent variables are log-transformed. Finally, Figure A13 and Table A12 report findings excluding the year 2009 in the event study and difference-in-differences specifications. Since Purdue Pharma ceased shipping the old formulations in August 2010, part of 2010 may be considered a treated period. These results confirm that the main findings are robust to these alternative specifications.

7 Mechanism

Figure 5: Allegations and Foster Care Placements



(a) Allegations



(b) Placements

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations and foster care placements per 1,000 children. All figures are based on a sample of 39 states, the same sample used in the analysis of false negatives.

As demonstrated in Section 3, an increase in the rate of false negatives, in response to a shock that increased maltreatment risk implies that CPS did not sufficiently increase the placement rates for at-risk children. This section explores this mechanism using the same subsample of 39 states used for the analysis of false negatives. Figure 5 presents event study plots where the dependent variables are maltreatment allegations (including all report sources) and foster care placements per 1,000 children. Allegations significantly increased following the reformulation. However, none of the coefficients for placement rates are statistically distinguishable from zero. To examine the magnitude of placement changes in the short and medium run and to compare these estimates with the changes in allegations, I estimate Equation 2 and present the results in Table 3, with additional heterogeneity analysis for placement rates over cases involving neglect, parental drug abuse, caretaker inability to cope, and physical abuse. Event study plots for placement rates by removal reasons are presented in Figure A10. Changes in placement rates for all type of allegations are statistically indistinguishable from zero in both the short and medium run. The magnitudes of the coefficients in terms of percentage changes from the baseline mean are also small compared to the changes in the allegations. The only types of cases where changes in the

Table 3: Allegations and Foster Care Placements

	(1) All Allegations	(2) All Placements	(3) Neglect Placements	(4) Drug Placements	(5) Inability to Cope Placements	(6) Physical Placements
Pre-reformulation	1.037	0.001	-0.030	-0.014	0.067	0.018
	(1.186)	(0.080)	(0.072)	(0.040)	(0.070)	(0.020)
Short-run	2.135**	0.026	0.010	0.012	0.004	0.018
	(1.051)	(0.066)	(0.058)	(0.027)	(0.026)	(0.012)
	[5.1%]	[0.8%]	[0.5%]	[1.5%]	[0.6%]	[3.6%]
Medium-run	5.205**	0.153	0.154*	0.118	-0.001	0.033*
	(2.225)	(0.115)	(0.076)	(0.080)	(0.045)	(0.018)
	[12.5%]	[4.7%]	[7.8%]	[14.9%]	[-0.2%]	[6.6%]
Mean (2010)	41.694	3.285	1.987	0.792	0.631	0.5
R-squared	0.870	0.901	0.883	0.816	0.702	0.816
Observations	506	506	506	506	506	506
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2. Columns (1) through (6) report the results for all allegations, placement rates for all allegations, neglect, parental drug abuse, caretaker inability to cope, and physical abuse, respectively. Regressions are based on a sample of 39 states, the same sample used in the analysis of false negatives, and they are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

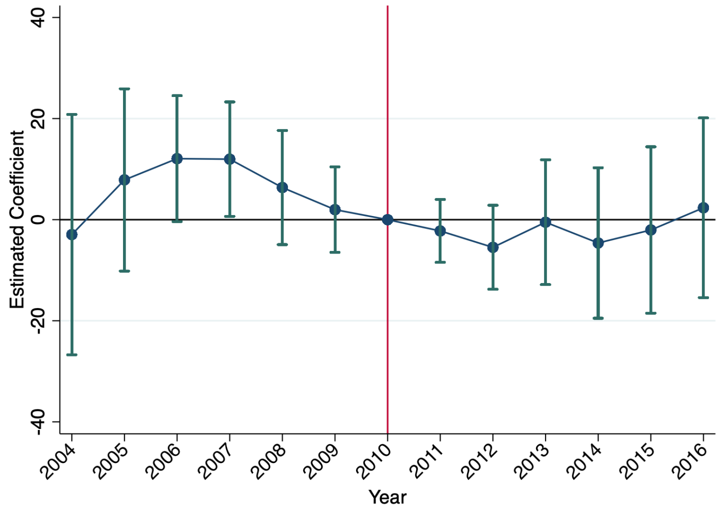
placement rates are statistically significant at the 10 percent level are neglect and physical abuse in the medium-run.

These results should be interpreted with caution, as the key determinant of changes in false negatives is not the overall placement rate ($\mathbb{P}(D_i = 1)$), but the placement rate for children with a potential for subsequent maltreatment ($\mathbb{P}(D_i = 1|Y_i^* = 1)$) as described in Section 3. Figure 5 and Table 3 suggest that the placement rate for all children, $\mathbb{P}(D_i = 1)$, may not have risen as much as the rise in the risk, $\mathbb{P}(Y_i^* = 1)$. This would provide a plausible empirical explanation for the rise in the false negative rate, assuming that the changes in the overall placement rate following the reformulation are similar to the changes in the placement rate for children at risk of subsequent maltreatment.

A potential explanation for the relatively inelastic changes in placement rates compared to changes in allegations could be a shortage of foster homes. Foster homes are typically categorized as either kinship care or unrelated foster families. When no foster homes are available, children may be placed in congregate care, which is generally considered a last resort (Bald et al., 2022*b*). Research has documented negative outcomes for children in congregate care, leading to a steady decline in congregate placement rates, as shown in Figure 6 (Lee and Thompson, 2008; Ryan et al., 2008; Robst, Armstrong and Dollard, 2011). However, trends in congregate placement rates have been similar between high- and low-exposure states. If foster home supply was more constrained in high-exposure states than in low-exposure states, congregate placement rates would likely increase more or decrease less in high-exposure states relative to low-exposure states. Figure 6 demonstrates that this is not the case, suggesting that a shortage of foster homes has not been the primary driver of trends in foster care placements.

Future research needs to delve more deeply into the factors that drive CPS foster care placement tendencies following the reformulation of OxyContin. Although this paper presents congregate placement rates as suggestive evidence that the supply of foster homes has not driven the results, future research may directly address the supply by compiling national licenses of foster families. One may also examine whether CPS responses were driven by changes in either skills or preferences, which was previously explored in a setting of radiologists diagnosing pneumonia (Chan, Gentzkow and Yu, 2022).

Figure 6: Congregate Placements per 1,000 Placements



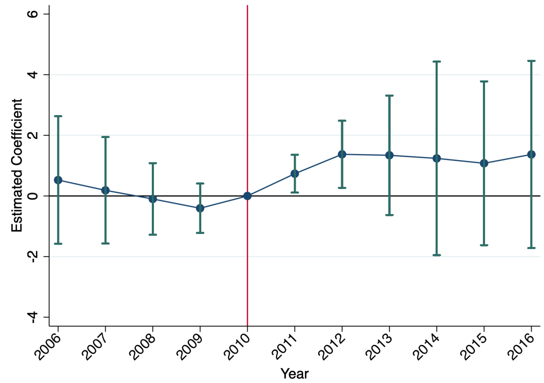
Notes. This reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. The dependent variable is congregate placements per 1,000 placements.

Another potential mechanism influencing CPS responses during times of crisis could be the adoption of alternative interventions beyond foster care placements. Children and families involved in child welfare investigations may receive postreponse services between the report data and up to 90 days after the disposition date. Postresponse services focus on ensuring the child's safety and are typically guided by an evaluation of the family's circumstances, including their needs for support and their strengths. It is possible that CPS accurately identified at-risk children and opted to provide postresponse services as an alternative to foster care placement. To redefine the treatment in Section 3, I consider the provision of postresponse services: $D_i^s \in \{0, 1\}$ denotes the services provision for child i where $D_i^s = 1$ indicates that postresponse service was provided to child i. Then false negative is redefined as follows:

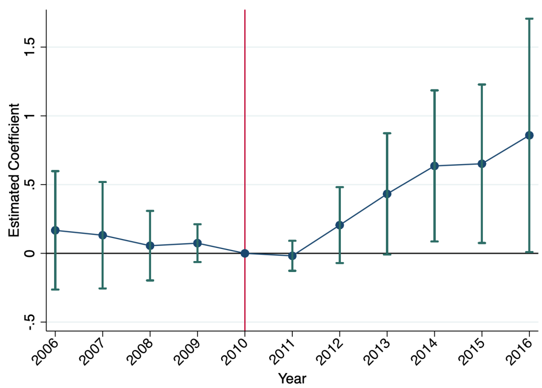
$$FN_i^s = \mathbb{1}(Y_i^* = 1, D_i^s = 0) \tag{3}$$

If CPS successfully identified at-risk children, provided them with postresponse services, and those services were effective in preventing subsequent maltreatment at home, the false negative rate would not increase following the reformulation of OxyContin.

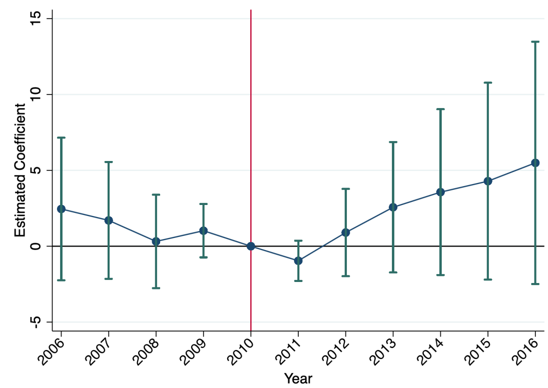
Figure 7: Service Provision and False Negatives



(a) Postresponse Services



(b) FN per 1,000 Children



(c) FN per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 children and allegations where the treatment is the provision of postresponse serivce.

Figure 7 and Table 4 present the event study and difference-in-differences results for the provision of postresponse services and false negatives. These analyses are based on data from 38 states, with South Dakota excluded due to its non-reporting of postresponse services. Additionally, the years 2005 and 2006 were excluded because a significant number of states did not report data during these periods. The findings indicate that the provision of postresponse services increased in the short term following the reformulation. Similar effects are observed in the medium term, although larger standard errors prevent rejecting the null hypothesis. However, false negatives per 1,000 children increased following the reformulation of OxyContin, consistent with results based on the definition of false negatives

Table 4: Difference-in-Differences Results for Services and False Negatives

	(1) Postresponse Services	(2) False Negatives per 1,000 Children	(3) False Negatives per 1,000 Allegations
Pre-reformulation	-0.019	0.094	1.205
	(0.631)	(0.133)	(1.485)
Short-run	1.143**	0.195*	0.754
	(0.514)	(0.108)	(1.075)
	[9.18%]	[11.6%]	[1.9%]
Medium-run	1.156	0.663**	4.022
	(1.377)	(0.302)	(3.051)
	[9.28%]	[39.3%]	[9.9%]
Mean (2010)	12.457	1.688	40.458
R-squared	0.847	0.733	0.754
Observations	417	417	417
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are postresponse services per 1,000 children and false negatives per 1,000 children and allegations. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

using foster care placements. These findings suggest that CPS may have faced challenges in effectively identifying at-risk children or that postresponse services were insufficient in preventing subsequent maltreatment at home.

The results in this section highlight a misalignment between the increased risk of maltreatment and CPS's capacity to identify and provide adequate support to at-risk children. The relatively small increase in the average placement rate provides suggestive evidence that children exposed to heightened maltreatment risks following the reformulation of OxyContin may have remained at home, leading to subsequent maltreatment. The increase in service provision rates suggests that CPS may have opted for alternative responses to address the rise in maltreatment risk rather than increasing foster care placements. However, the concurrent rise in false negative rates, despite the provision of services, indicates that either some children at risk due to the reformulation were not identified by CPS or that the services provided were ineffective in preventing subsequent maltreatment.

8 Conclusion

Child maltreatment is associated with a wide range of negative socioeconomic outcomes. The primary objective of child protective services is to intervene and protect at-risk children from further traumatic experiences at home. Removing children from environments where they are at risk of maltreatment becomes particularly crucial during crises that significantly heighten their exposure to such risks.

This paper examines foster care decisions of CPS using the reformulation of OxyContin - one of the largest disruptions in the supply of abusable prescription opioids to date - as a quasi-random shock to maltreatment risk. Levering cross-state variation in pre-reformulation OxyContin misuse rates, I present two key findings. First, maltreatment allegations significantly increased following the reformulation of OxyContin, consistent with previous studies that document the unintended consequences of supply-side drug policies amid the opioid epidemic. Second, more at-risk children were left at home following the intervention. This misalignment between an increase in maltreatment risk and CPS foster care decisions is not primarily driven by the shortage of foster homes or an increased reliance on post-response services.

The findings of this paper emphasize the critical importance of responsive foster care placement policies during periods of heightened maltreatment risk. Along with a growing body of literature documenting the positive causal effects of foster care placements on children's long-term outcomes, these results underscore the need for child welfare systems to adapt and respond effectively in times of crisis, such as those caused by disruptions like the opioid epidemic. Specifically, the misalignment between increased maltreatment risk and foster care placement decisions highlights potential gaps in CPS's capacity to address severe cases of maltreatment, which may leave vulnerable children without adequate protection.

Furthermore, this paper reconciles two original but seemingly contradictory studies on the impacts of the opioid epidemic on child welfare by proposing that severe cases of maltreatment during the crisis may have been overlooked by CPS. This oversight underscores the importance of strengthening the child welfare system to ensure it can identify and intervene in such cases, particularly during public health emergencies that increase maltreatment risks.

These findings call for enhanced support for the child welfare system, including investments in resources, training, and infrastructure that enable CPS to be more responsive during crises. Building a system capable of scaling foster care placements and other interventions when more children are exposed to maltreatment risk is essential for safeguarding the well-being of vulnerable children. Developing policies that align the provision of services with periods of heightened need can help mitigate the consequences of child maltreatment.

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Online Appendix

Crisis Response in Child Protection: Examining Foster Care Decisions During the Opioid Epidemic

Jeongsoo Suh

A First Stage Regression

Table A1: First Stage Regressions

	(1)	(2)
Exp_s	-0.184***	-0.121*
	(0.046)	(0.060)
Unemployment		0.048
		(0.046)
Labor force participation		0.033*
		(0.019)
Percent White		-0.002
		(0.007)
Percent Black		0.022**
		(0.009)
Percent Hispanic		0.009
		(0.007)
Percent Female		-0.132
		(0.120)
Percent age 0 to 19		-0.022
		(0.052)
Percent age 20 to 24		-0.056
		(0.146)
Percent age 25 to 34		0.032
		(0.106)
Percent age 35 to 44		-0.080
		(0.139)
Percent age 45 to 54		0.300***
		(0.105)
Percent age 55 to 64		-0.048
		(0.162)
Constant	-0.156***	1.702
	(0.044)	(8.623)
R-squared	0.330	0.658
F Statistics	16.304	11.949
Observations	49	49

Notes. This table presents point estimates and standard errors from weighted least squares (WLS) regressions of the change in OxyContin misuse rates from 2008 to 2012 on the pre-reformulation rates of OxyContin misuse. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Supplemental Summary Statistics

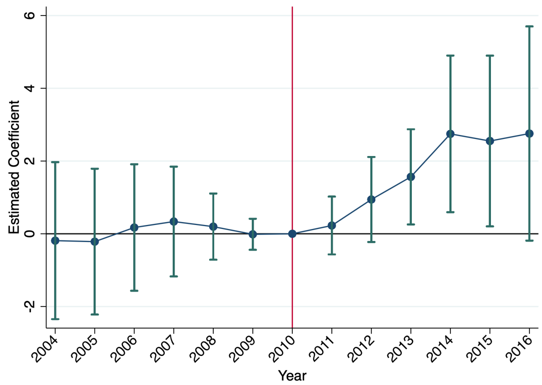
Table A2: Summary Statistics for Maltreatment Allegations

Variable	All Allegations	Professional Allegations
Panel A: Maltreatment Types		
Neglect	60.4	53.1
Physical Abuse	21.8	24.1
Sexual Abuse	7.5	8.4
Psychological/Emotional Maltreatment	6.9	7.0
Medical Neglect	2.4	2.7
Other	9.5	9.1
Panel B: Child Charateristics		
White	60.0	58.5
Black	25.4	26.0
Male	49.6	49.6
Female	49.8	49.9
Young (age < 7)	45.8	43.3
Old (age ≥ 7)	53.5	56.3
Panel C: Report Sources		
Education Personnel	16.7	29.6
Legal Personnel	16.5	29.4
Social Services Personnel	10.2	18.2
Medical Personnel	7.5	13.3
Mental Health Personnel	4.7	8.3
Child Daycare Provider	0.7	1.2
Anonymous Reporter	9.2	-
Relatives	7.3	-
Parent	6.5	-
Friends/Neighbors	5.2	-
Substitute Care Provider	0.4	-
Alleged Victim	0.4	-
Alleged Perpetrator	0.1	-
Unknown	14.6	-

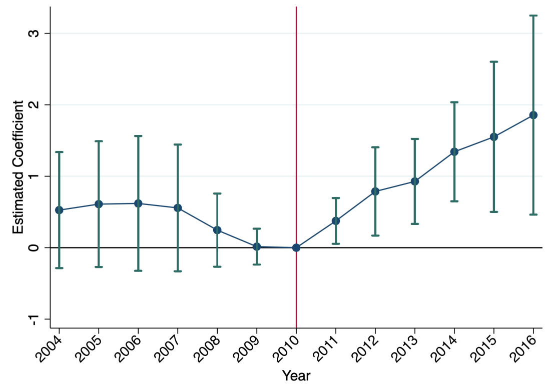
Notes. This table reports the percentage of allegations by maltreatment types, child characteristics, and report sources, separately for all allegations and for allegations made by professionals during the sample period from 2004 to 2016. Professional allegations refer to those reported by education personnel, legal personnel, social services personnel, medical personnel, mental health providers, and child daycare providers.

C Allegations by Maltreatment Types and Report Sources

Figure A1: Allegations Reported by Professionals by Maltreatment Types



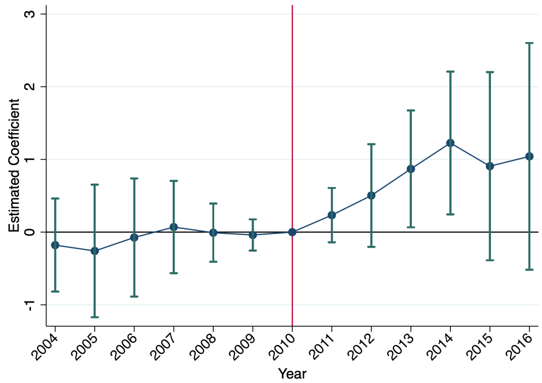
(a) Neglect



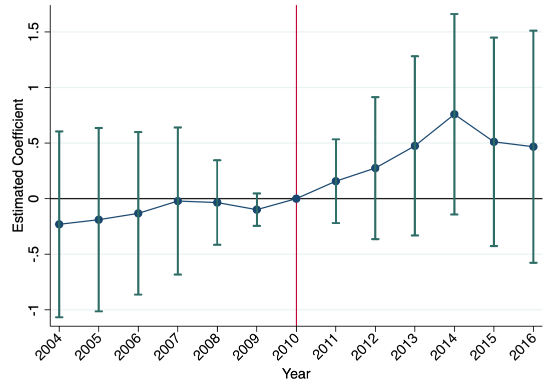
(b) Physical Abuse

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are neglect and physical abuse per 1,000 children reported by professionals. Regressions are weighted by child population.

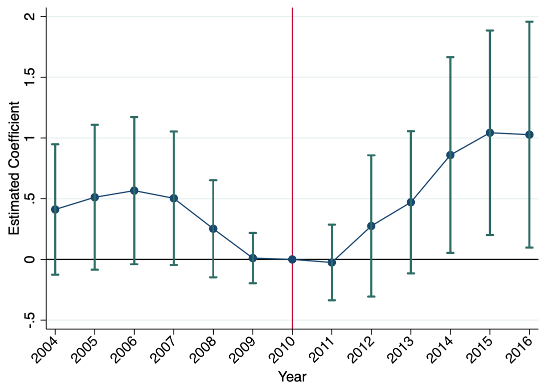
Figure A2: Maltreatment Allegations by Occupation



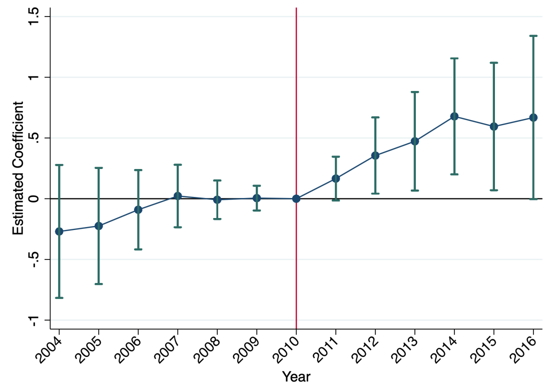
(a) Education Personnel



(b) Legal Personnel



(c) Social Services Personnel



(d) Medical Personnel

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 1,000 children reported by education, legal, social services, and medical personnel. Regressions are weighted by child population.

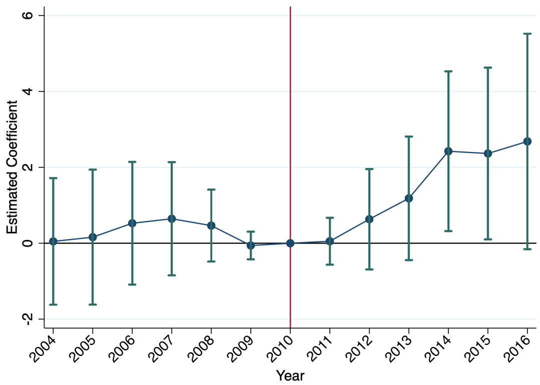
Table A3: Allegations by Maltreatment Type and Report Source

	(1) Neglect	(2) Physical	(3) Education	(4) Legal	(5) Social Services	(6) Medical
Pre-reformulation	0.071	0.402	-0.066	-0.107	0.355	-0.077
	(0.633)	(0.320)	(0.264)	(0.253)	(0.215)	(0.127)
Short-run	0.886*	0.690***	0.524*	0.298	0.237	0.323**
	(0.446)	(0.238)	(0.282)	(0.284)	(0.228)	(0.129)
	[6.7%]	[11.3%]	[7.7%]	[4.2%]	[5.2%]	[10.3%]
Medium-run	2.606**	1.555***	1.025	0.566	0.958**	0.622**
	(1.191)	(0.505)	(0.615)	(0.461)	(0.423)	(0.259)
	[19.7%]	[25.5%]	[15.0%]	[7.9%]	[20.9%]	[19.8%]
Mean (2010)	13.237	6.105	6.839	7.122	4.58	3.146
R-squared	0.847	0.713	0.845	0.929	0.862	0.858
Observations	634	634	634	634	634	634
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

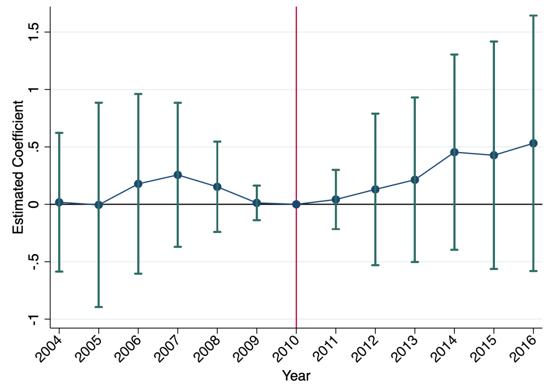
Notes. This table reports point estimates and standard errors from Equation 2, where dependent variables are maltreatment allegations reported by professionals per 1,000 children, broken down by report type and source. Regressions are weighted by child population. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D Allegations by Child Charateristics

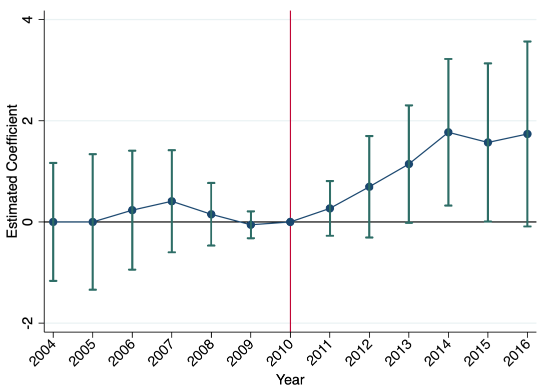
Figure A3: Maltreatment Allegations by Child Characteristics



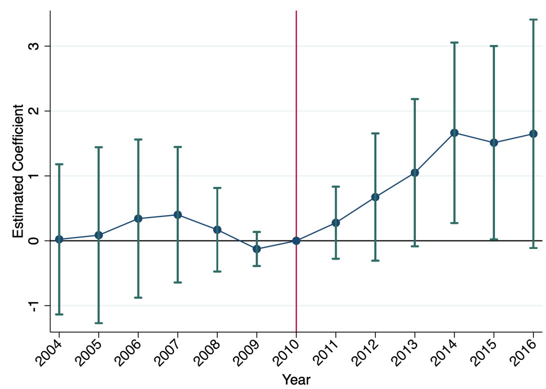
(a) White



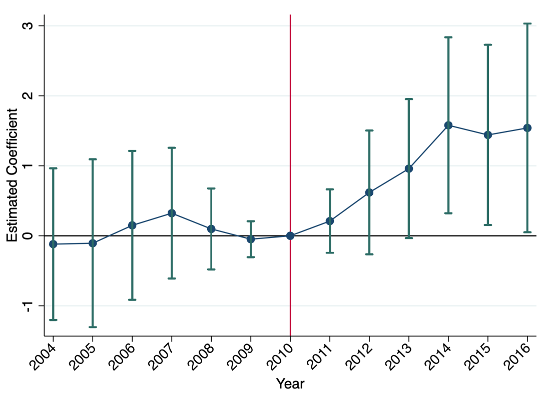
(b) Black



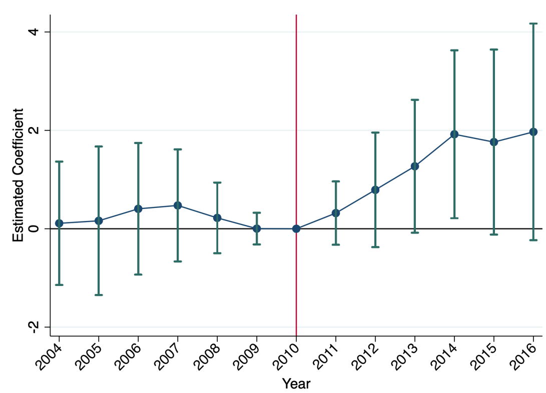
(c) Male



(d) Female



(e) Young



(f) Old

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations reported by professionals, broken down by child charateristics. Regressions are weighted by child population.

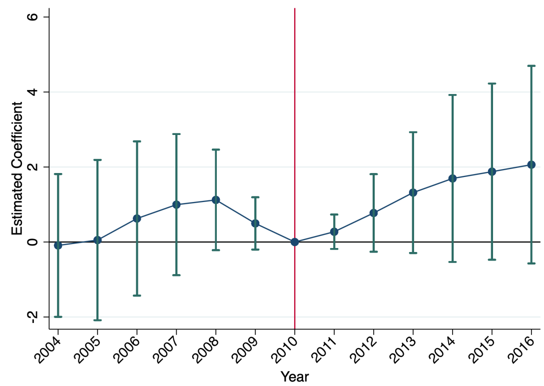
Table A4: Maltreatment Allegations by Child Characteristics

	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
Pre-reformulation	0.304	0.105	0.129	0.147	0.060	0.230
	(0.563)	(0.248)	(0.394)	(0.403)	(0.371)	(0.448)
Short-run	0.603	0.124	0.688*	0.655	0.583	0.778
	(0.528)	(0.254)	(0.408)	(0.404)	(0.352)	(0.475)
	[4.2%]	[2.0%]	[5.8%]	[5.5%]	[5.5%]	[5.9%]
Medium-run	2.421**	0.455	1.647**	1.569**	1.476**	1.834*
	(1.145)	(0.473)	(0.773)	(0.741)	(0.642)	(0.926)
	[16.8%]	[7.2%]	[13.9%]	[13.1%]	[13.9%]	[13.8%]
Mean (2010)	14.391	6.291	11.882	11.975	10.582	13.271
R-squared	0.886	0.922	0.888	0.884	0.894	0.881
Observations	621	621	634	634	634	634
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

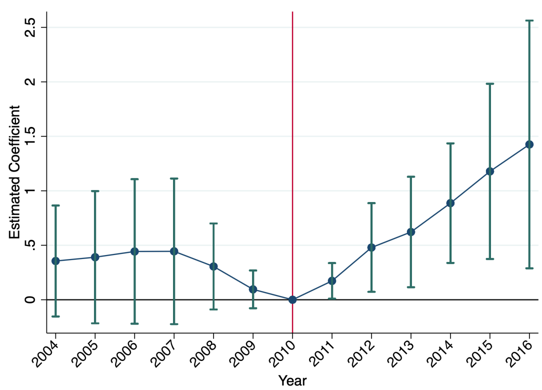
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are maltreatment allegations reported by professionals, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E Allegations by Non-Professionals

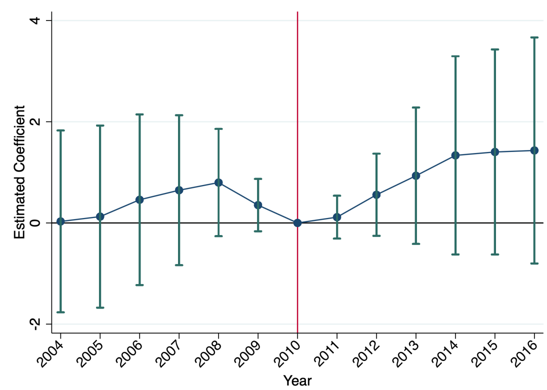
Figure A4: Maltreatment Allegations Reported by Non-Professionals



(a) All Types



(b) Physical Abuse



(c) Neglect

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations reported by non-professionals which include substitute care provider, alleged victim, parent, relatives, friends/neighbors, alleged perpetrator, and anonymous reporter. Regressions are weighted by child population.

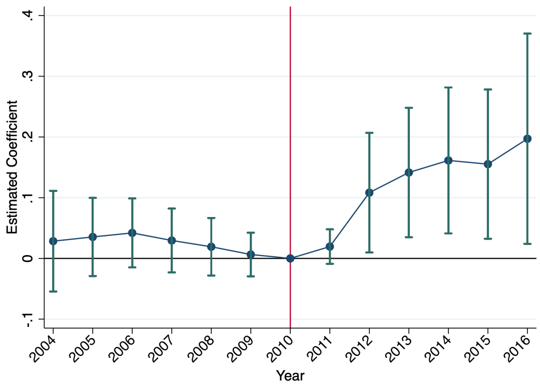
Table A5: Maltreatment Allegations Reported by Non-Professionals

	(1) All Types	(2) Neglect	(3) Physical
Pre-reformulation	0.583	0.432	0.328
	(0.743)	(0.614)	(0.232)
Short-run	0.757*	0.514	0.416**
	(0.431)	(0.337)	(0.168)
	[6.0%]	[5.5%]	[15.9%]
Medium-run	1.781	1.327	1.132***
	(1.142)	(0.989)	(0.385)
	[14.1%]	[14.2%]	[43.1%]
Mean (2010)	12.665	9.342	2.624
R-squared	0.878	0.853	0.761
Observations	634	634	634
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

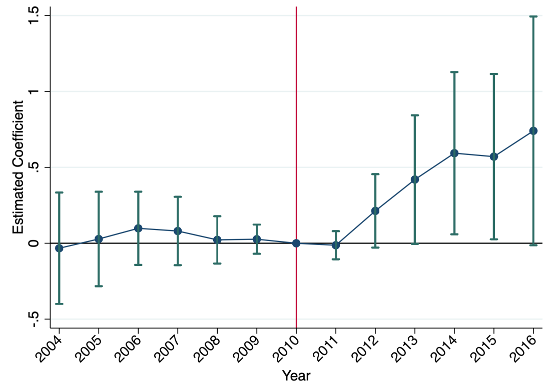
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are allegations per 1,000 children reported by non-professionals, broken down by maltreatment types. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

F False Negatives by Maltreatment Types and Child Charateristics

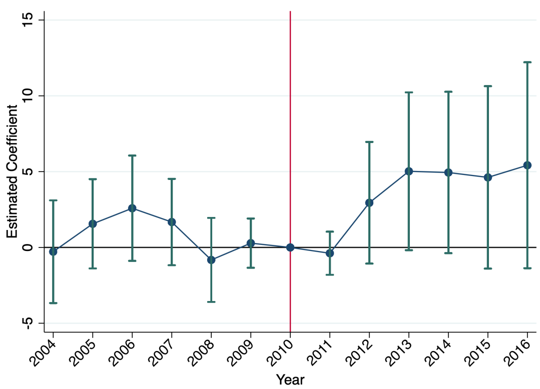
Figure A5: FN per 1,000 Children and Allegations by Maltreatment Types



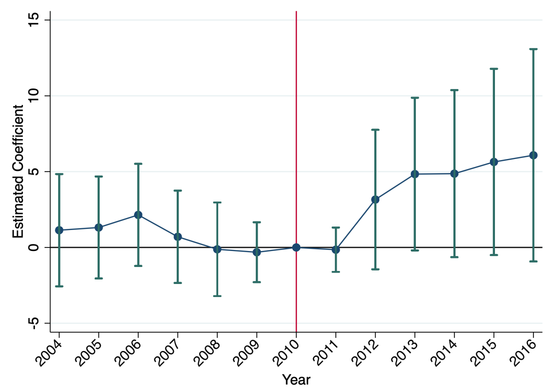
(a) Neglect per 1,000 Children



(b) Physical Abuse per 1,000 Children



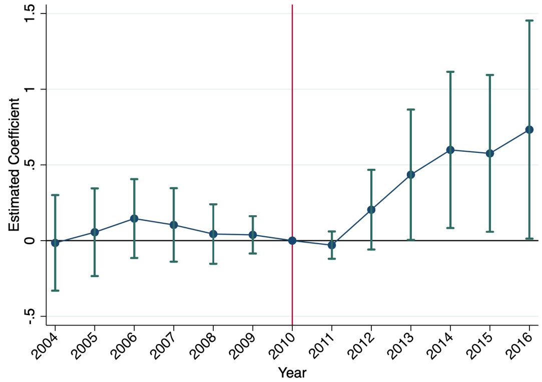
(c) Neglect per 1,000 Allegations



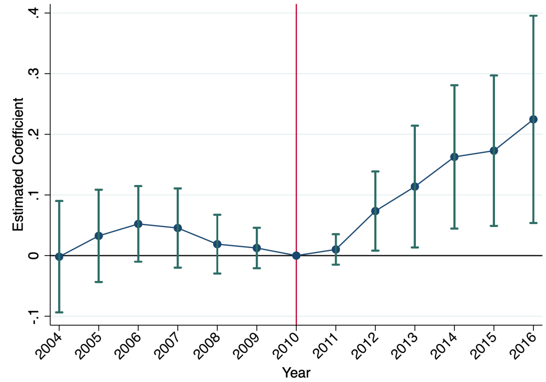
(d) Physical Abuse per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 children and allegations by maltreatment types. Regressions are weighted by child population.

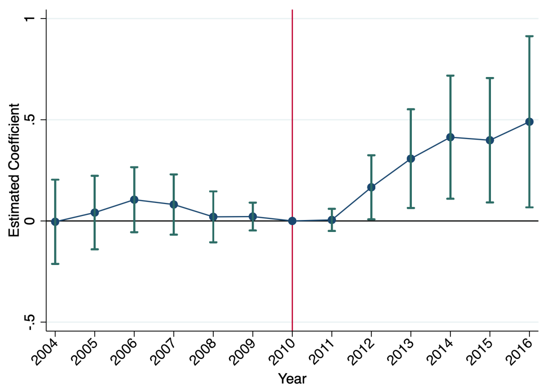
Figure A6: False Negatives per 1,000 Children by Child Characteristics



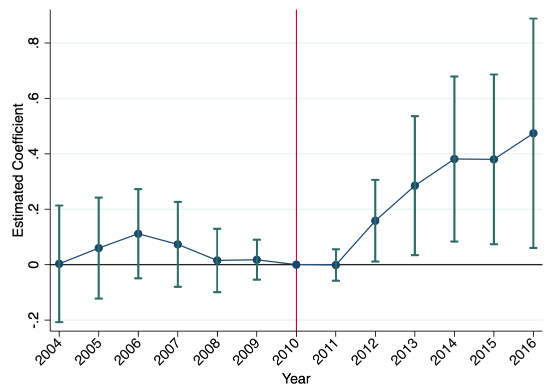
(a) White



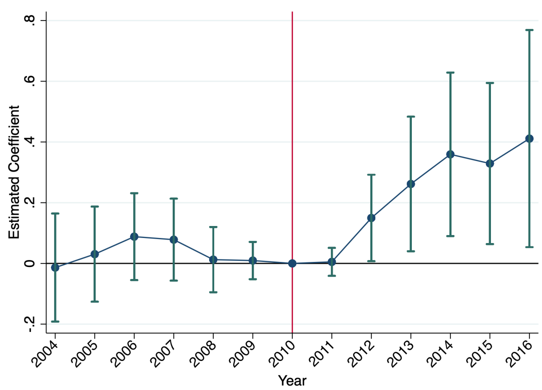
(b) Black



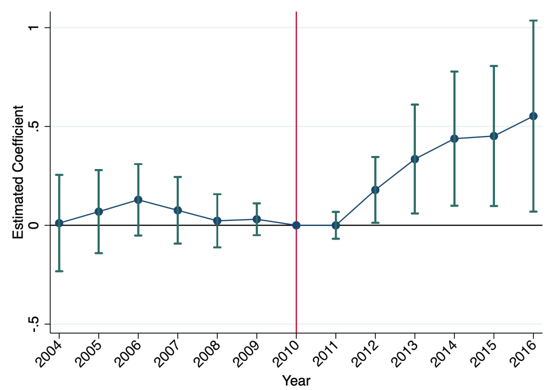
(c) Male



(d) Female



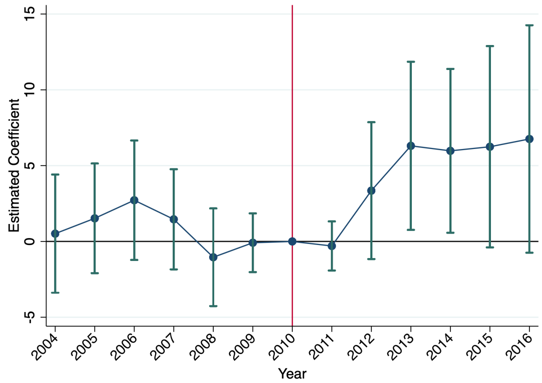
(e) Young



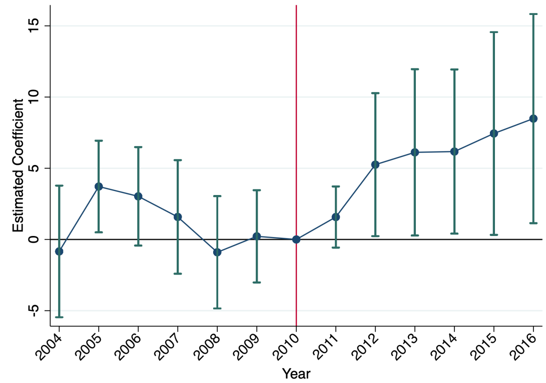
(f) Old

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 children by child characteristics. Regressions are weighted by child population.

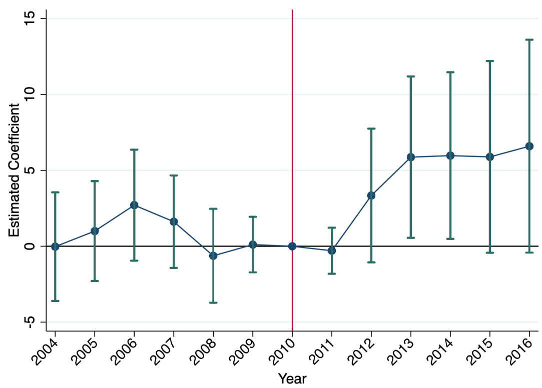
Figure A7: False Negatives per 1,000 Allegations by Child Characteristics



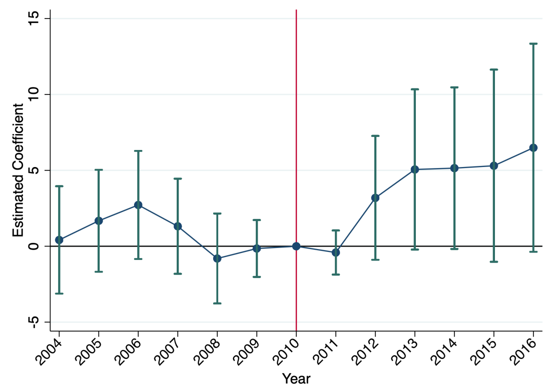
(a) White



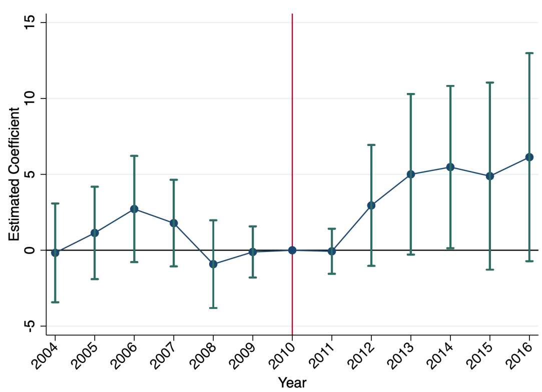
(b) Black



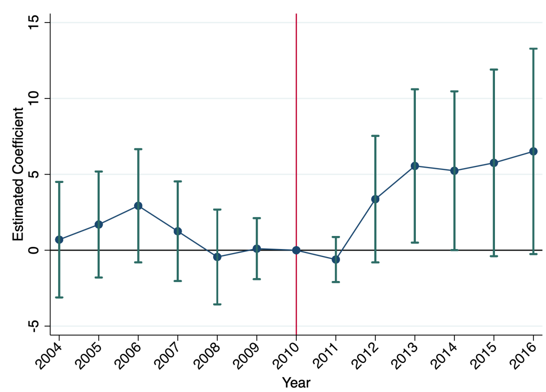
(c) Male



(d) Female



(e) Young



(f) Old

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations by child characteristics. Regressions are weighted by child population.

Table A6: FN per 1,000 Children by Maltreatment Types and Child Characteristics

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.036	0.025	0.060	0.025	0.042	0.043	0.032	0.053
	(0.093)	(0.021)	(0.096)	(0.025)	(0.060)	(0.059)	(0.051)	(0.068)
Short-run	0.199*	0.088**	0.195*	0.064**	0.155**	0.143**	0.134**	0.166**
	(0.105)	(0.035)	(0.111)	(0.026)	(0.065)	(0.064)	(0.060)	(0.070)
	[14.1%]	[15.5%]	[13.2%]	[13.6%]	[13.3%]	[12.1%]	[12.5%]	[13.0%]
Medium-run	0.604**	0.163**	0.604**	0.178***	0.413**	0.392**	0.349**	0.458**
	(0.288)	(0.064)	(0.274)	(0.064)	(0.162)	(0.159)	(0.139)	(0.184)
	[42.8%]	[28.8%]	[40.9%]	[37.8%]	[35.3%]	[33.3%]	[32.6%]	[35.8%]
Mean (2010)	1.412	0.566	1.477	0.471	1.169	1.177	1.07	1.278
R-squared	0.728	0.757	0.776	0.877	0.768	0.765	0.775	0.771
Observations	506	506	506	506	506	506	506	506
α_s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 children by maltreatment types and child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: FN per 1,000 Allegations by Maltreatment Types and Child Characteristics

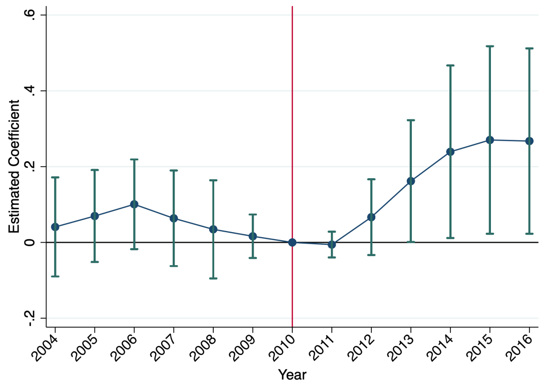
	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.743	0.658	0.696	0.976	0.700	0.707	0.627	0.893
	(1.071)	(1.241)	(1.330)	(1.477)	(1.243)	(1.201)	(1.100)	(1.319)
Short-run	2.453	2.551	3.033*	4.257**	2.882*	2.537	2.559	2.684*
	(1.608)	(1.689)	(1.751)	(1.908)	(1.684)	(1.643)	(1.647)	(1.569)
	[4.5%]	[4.5%]	[5.2%]	[7.5%]	[5.1%]	[4.5%]	[4.7%]	[4.5%]
Medium-run	4.662	5.231*	5.943*	7.037**	5.765*	5.300*	5.171*	5.456*
	(2.822)	(2.915)	(3.057)	(3.185)	(2.934)	(2.884)	(2.866)	(2.809)
	[8.5%]	[9.3%]	[10.1%]	[12.3%]	[10.2%]	[9.4%]	[9.6%]	[9.2%]
Mean (2010)	54.789	56.392	58.865	57.106	56.749	56.575	54.056	59.215
R-squared	0.804	0.779	0.810	0.781	0.814	0.811	0.816	0.805
Observations	506	506	506	506	506	506	506	506
α_s	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 allegations by maltreatment types and child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.

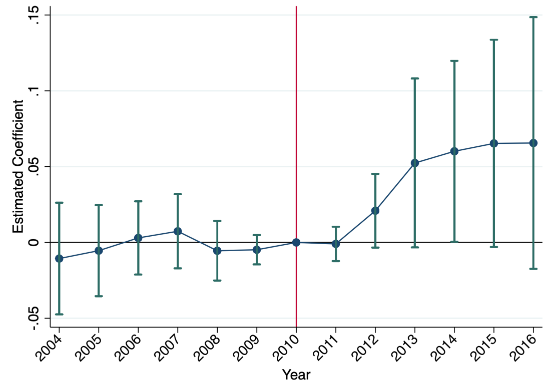
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G Alternative Measures of False Negatives

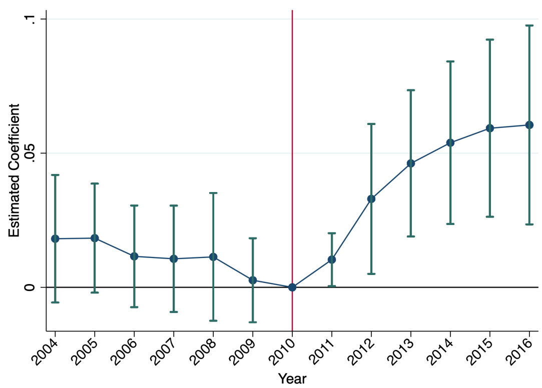
Figure A8: False Negatives per 1,000 Children - Alternative Measures



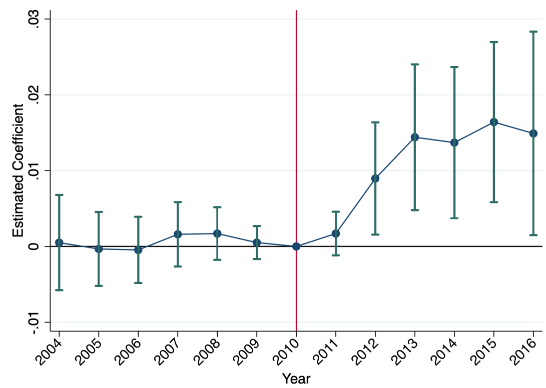
(a) All Types Substantiated



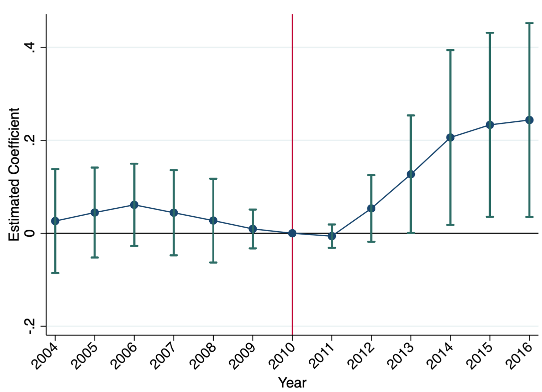
(b) All Types Placed in Foster Care



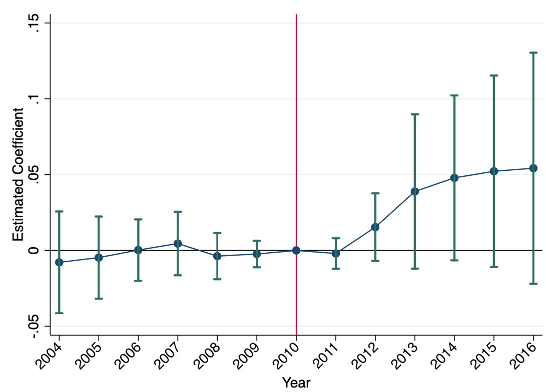
(c) Physical Abuse Substantiated



(d) Physical Abuse Placed in Foster Care



(e) Neglect Substantiated



(f) Neglect Placed in Foster Care

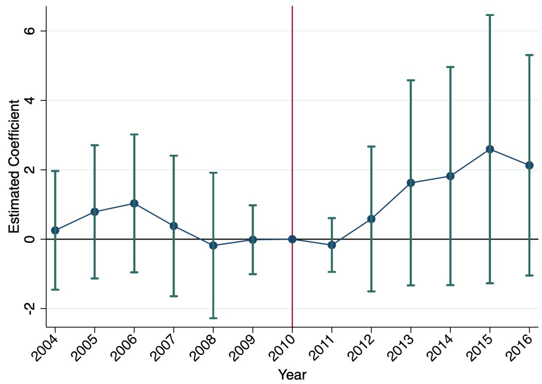
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 children based on alternative measures. Regressions are weighted by child population.

Table A8: False Negatives per 1,000 Children - Alternative Measures

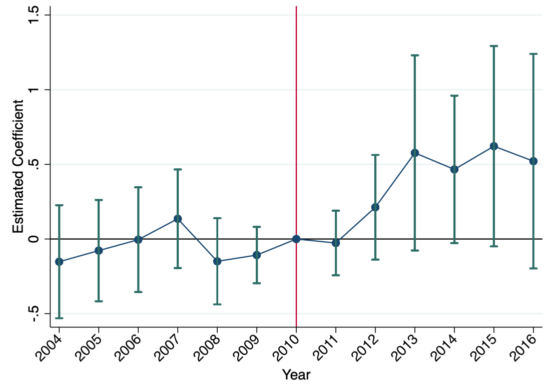
	(1) All Types Substantiated	(2) Neglect Substantiated	(3) Physical Substantiated	(4) All Types Placed	(5) Neglect Placed	(6) Physical Placed
Pre-reformulation	0.050	0.033	0.011	-0.003	-0.002	0.001
	(0.052)	(0.039)	(0.009)	(0.010)	(0.009)	(0.002)
Short-run	0.072	0.056	0.029***	0.023*	0.017	0.008***
	(0.045)	(0.033)	(0.010)	(0.014)	(0.012)	(0.003)
	[11.3%]	[13.2%]	[21.3%]	[14.7%]	[15.6%]	[25.8%]
Medium-run	0.249**	0.219**	0.056***	0.060*	0.049	0.014***
	(0.114)	(0.094)	(0.015)	(0.033)	(0.031)	(0.005)
	[39.0%]	[51.7%]	[41.2%]	[38.5%]	[45.0%]	[45.2%]
Mean (2010)	0.639	0.424	0.136	0.156	0.109	0.031
R-squared	0.815	0.794	0.850	0.693	0.682	0.664
Observations	506	506	506	506	506	506
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 children by maltreatment types. Panel A reports estimates based on the following measure for false negatives: a child was initially left at home, subsequently reported by professionals within 6 months and the case was substantiated. Panel B reports estimates based on the following measure for false negatives: a child was initially left at home, subsequently reported by professionals within 6 months and the child was removed from home. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

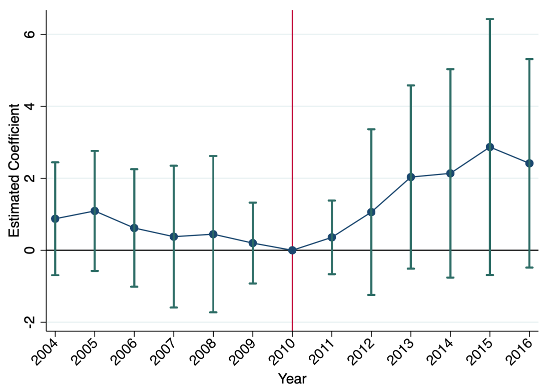
Figure A9: False Negatives per 1,000 Allegations - Alternative Measures



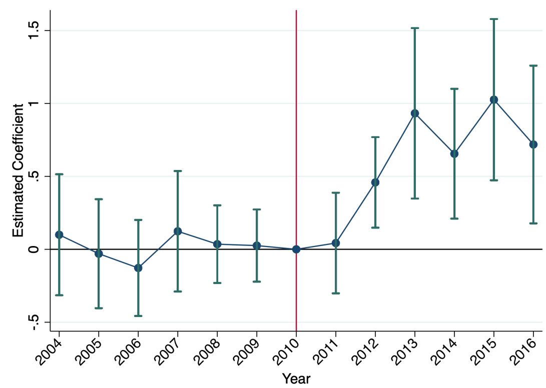
(a) All Types Substantiated



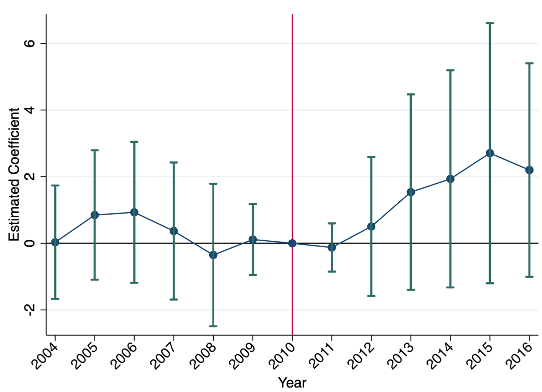
(b) All Types Placed in Foster Care



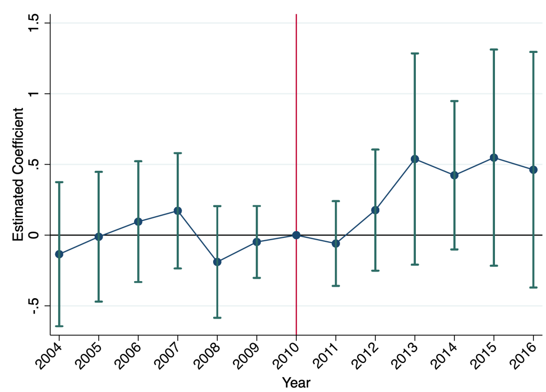
(c) Physical Abuse Substantiated



(d) Physical Abuse Placed in Foster Care



(e) Neglect Substantiated



(f) Neglect Placed in Foster Care

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations based on alternative measures. Regressions are weighted by child population.

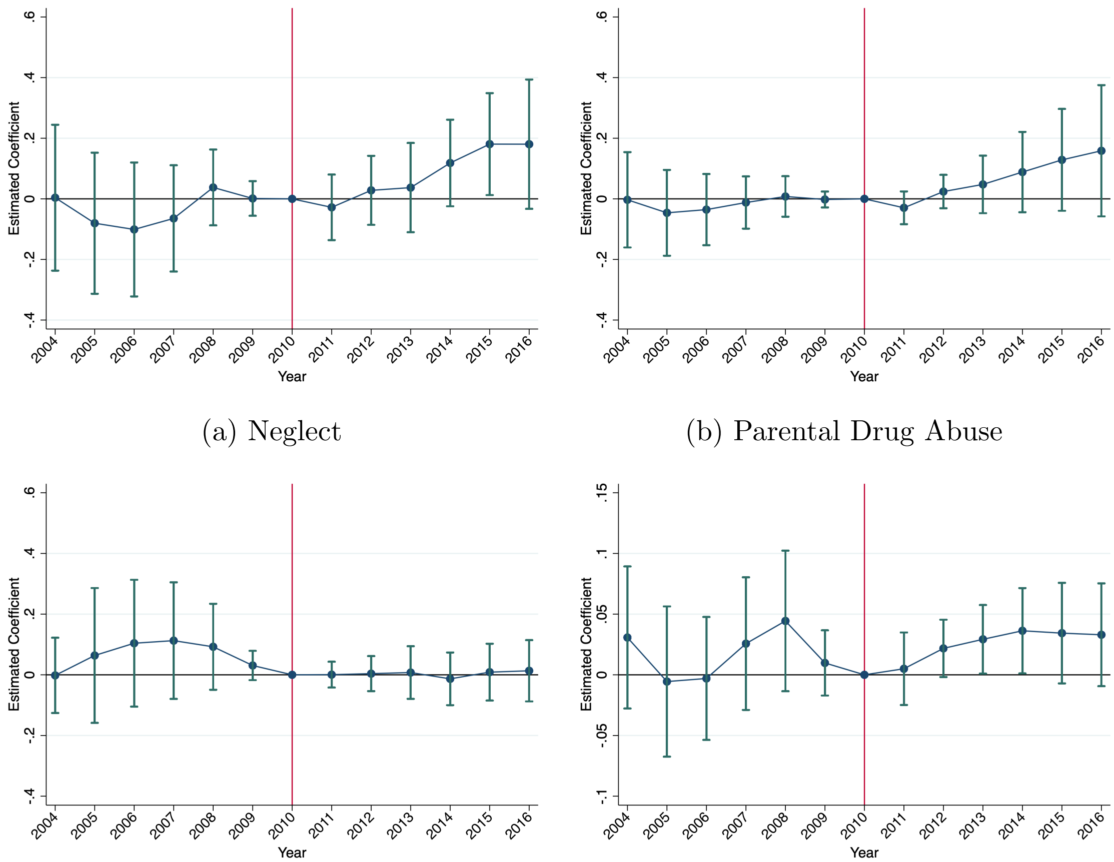
Table A9: False Negatives per 1,000 Allegations - Alternative Measures

	(1) All Types Substantiated	(2) Neglect Substantiated	(3) Physical Substantiated	(4) All Types Placed	(5) Neglect Placed	(6) Physical Placed
Pre-reformulation	0.317	0.275	0.550	-0.063	-0.025	0.021
	(0.796)	(0.800)	(0.745)	(0.126)	(0.164)	(0.131)
Short-run	0.660	0.620	1.134	0.245	0.210	0.464***
	(0.928)	(0.911)	(0.948)	(0.180)	(0.209)	(0.156)
	[4.3%]	[3.8%]	[8.4%]	[6.6%]	[5.0%]	[15.2%]
Medium-run	2.080	2.188	2.397	0.498*	0.440	0.751***
	(1.618)	(1.644)	(1.491)	(0.286)	(0.319)	(0.234)
	[13.6%]	[13.3%]	[17.7%]	[13.3%]	[10.4%]	[24.6%]
Mean (2010)	15.316	16.448	13.56	3.736	4.217	3.058
R-squared	0.864	0.866	0.846	0.798	0.751	0.652
Observations	506	506	506	506	506	506
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 allegations by maltreatment types. Panel A reports estimates based on the following measure for false negatives: a child was initially left at home, subsequently reported by professionals within 6 months and the case was substantiated. Panel B reports estimates based on the following measure for false negatives: a child was initially left at home, subsequently reported by professionals within 6 months and the child was removed from home. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

H Heterogeneity Analysis for Placement Rates

Figure A10: Placements per 1,000 Children by Removal Reason



(a) Neglect

(b) Parental Drug Abuse

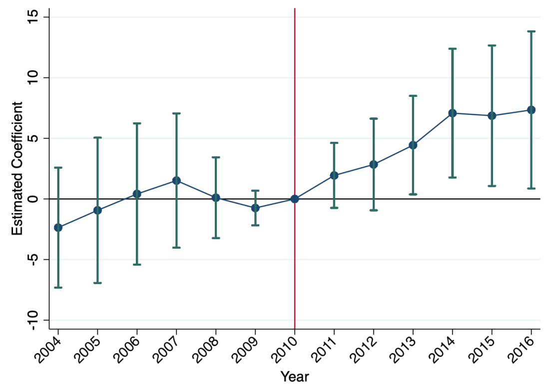
(c) Caretaker Inability to Cope

(d) Physical Abuse

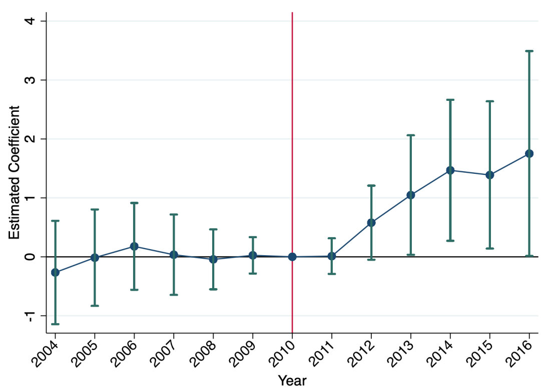
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are foster care placements per 1,000 children by removal reason. Figures (a) through (d) report results for neglect, parental drug abuse, caretaker inability to cope, and physical abuse, respectively.

I Binary Treatment

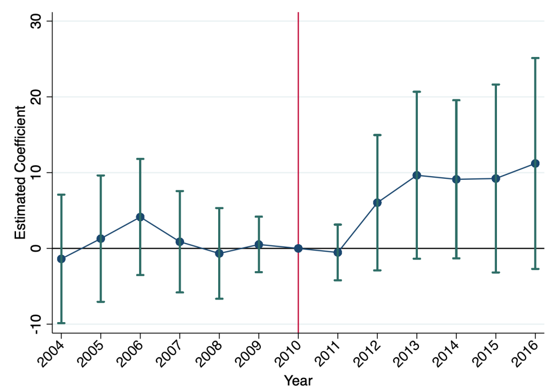
Figure A11: Maltreatment Allegations and False Negatives - Binary Treatment



(a) Allegations by Professionals



(b) False Negatives per 1,000 Children



(c) False Negatives per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations reported by professionals, false negatives per 1,000 children, and false negatives per 1,000 allegations. Exposure measure in Equations 1 is defined as an indicator which takes the value of 1 if the state's pre-reformulation rate of OxyContin misuse is above the median. Regressions are weighted by child population.

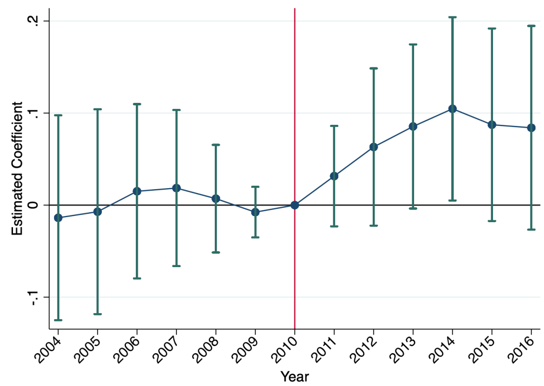
Table A10: Difference-in-Differences Results for Allegations and False Negatives - Binary Treatment

	(1) Professional Allegations	(2) False Negatives per 1,000 Children	(3) False Negatives per 1,000 Allegations
Pre-reformulation	-0.272	-0.016	0.719
	(2.002)	(0.281)	(2.852)
Short-run	3.045*	0.541**	4.991
	(1.548)	(0.262)	(3.568)
	[10.7%]	[19.5%]	[8.4%]
Medium-run	7.009**	1.507**	9.561
	(2.872)	(0.676)	(5.900)
	[24.5%]	[54.4%]	[16.2%]
Mean (2010)	28.589	2.769	59.123
R-squared	0.890	0.767	0.814
Observations	634	506	506
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

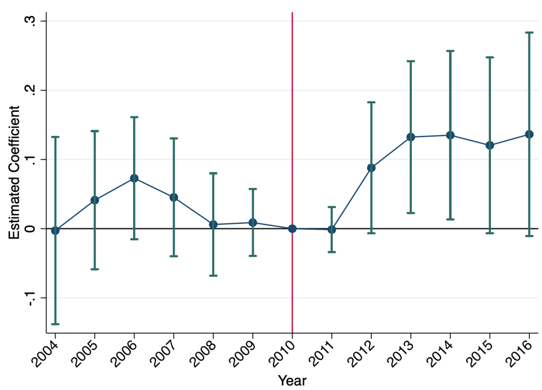
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are maltreatment allegations per 1,000 children reported by professionals and false negatives per 1,000 children and allegations. Exposure measure in Equations 2 is defined as an indicator which takes the value of 1 if the state's pre-reformulation rate of OxyContin misuse is above the median. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J Logarithmic Transformation

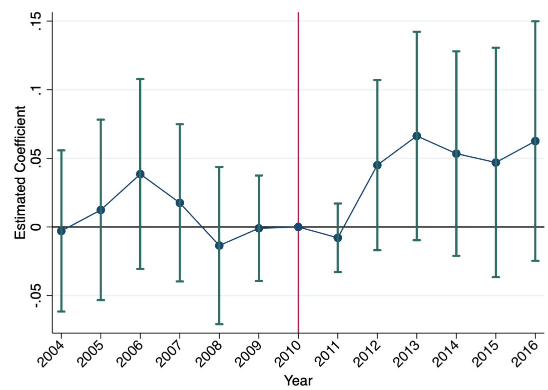
Figure A12: Maltreatment Allegations and False Negatives - Logarithm



(a) Allegations by Professionals



(b) False Negatives per 1,000 Children



(c) False Negatives per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are logarithms of maltreatment allegations reported by professionals, false negatives per 1,000 children, and false negatives per 1,000 allegations. Regressions are weighted by child population.

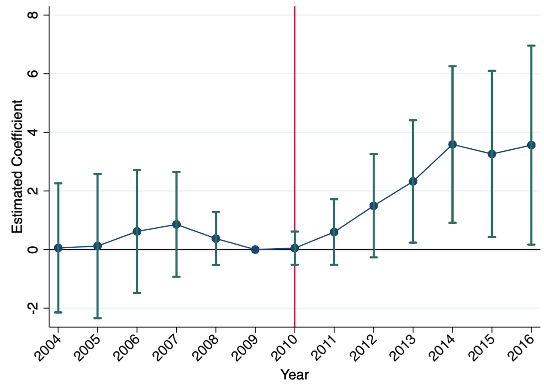
Table A11: Difference-in-Differences Results for Allegations and False Negatives - Logarithm

	(1) Professional Allegations	(2) False Negatives per 1,000 Children	(3) False Negatives per 1,000 Allegations
Pre-reformulation	0.003	0.027	0.007
	(0.035)	(0.032)	(0.024)
Short-run	0.059	0.071**	0.033
	(0.036)	(0.034)	(0.024)
Medium-run	0.089*	0.122*	0.050
	(0.051)	(0.062)	(0.038)
R-squared	0.851	0.855	0.811
Observations	634	506	506
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

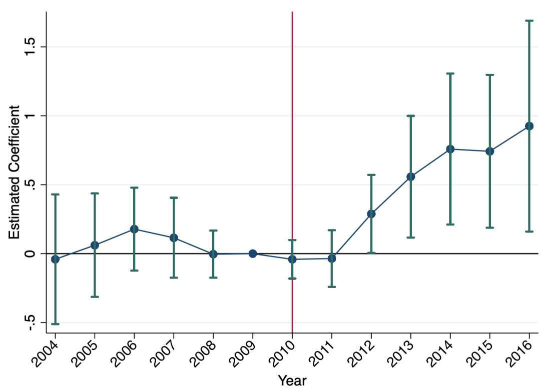
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are logarithms of maltreatment allegations per 1,000 children reported by professionals and false negatives per 1,000 children and allegations. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

K Results for Year 2009 Normalized

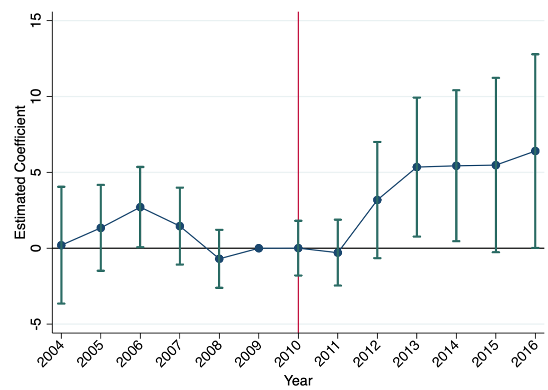
Figure A13: Maltreatment Allegations and False Negatives - Year 2009 Normalized



(a) Allegations by Professionals



(b) False Negatives per 1,000 Children



(c) False Negatives per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations reported by professionals, false negatives per 1,000 children, and false negatives per 1,000 allegations. Regressions are weighted by child population.

Table A12: Difference-in-Differences Results for Allegations and False Negatives - Year 2009 Omitted

	(1) Professional Allegations	(2) False Negatives per 1,000 Children	(3) False Negatives per 1,000 Allegations
Pre-reformulation	0.435	0.062	0.978
	(0.855)	(0.145)	(1.123)
Short-run	0.697*	0.071	0.987
	(0.393)	(0.079)	(0.992)
	[2.9%]	[3.0%]	[1.7%]
Medium-run	3.051**	0.712**	5.511**
	(1.247)	(0.268)	(2.549)
	[12.9%]	[30.5%]	[9.7%]
Mean (2009)	23.661	2.331	56.566
R-squared	0.887	0.770	0.819
Observations	634	506	506
α_s	Yes	Yes	Yes
γ_t	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are maltreatment allegations per 1,000 children reported by professionals and false negatives per 1,000 children and allegations. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2009 are reported in square brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

L Policy Variables and Sample Construction

Table A13: Years in Which Must-Access PDMPs Went into Effect for Adopting States

Year	**States**
2006	NV
2010	OK
2011	OH
2012	DE, KY, NM, WV
2013	MA, NY, TN, VT
2014	IN, LA
2015	CT, NJ, VA
2016	NH, RI

Notes. Must-access PDMP implementation dates are based on Sacks et al. (2021) with five corrections made by Evans et al. (2021).