Child Protection in Crisis: Examining Foster Care Decisions Following the Opioid Supply Disruption*

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November 15, 2024

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Abstract

Child protective services (CPS) plays a critical role in protecting children exposed to maltreatment risk at home. Effective CPS policy responses during crises, when child maltreatment risk is heightened, are essential for safeguarding vulnerable children from severe harm. This paper examines foster care decisions of CPS using the reformulation of OxyContin - one of the largest opioid supply disruptions in the United States - as a quasi-random shock to child maltreatment risk. Leveraging cross-state variation in pre-reformulation OxyContin misuse rates as a measure of differential exposure to the intervention, I find that states with higher initial OxyContin misuse rates experienced relatively larger increases in maltreatment allegations from professional sources, including educational, medical, and social services personnel. However, while more children were exposed to maltreatment risk following the opioid supply disruption, 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 — particularly in states with higher initial OxyContin misuse rates. These findings suggest a misalignment between increased maltreatment risk and CPS placement decisions during this period of heightened opioid-related family instability.

*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

In 2022, more than 4.2 million child maltreatment allegations were reported in the United States. Following the investigations, around 556,000 children were confirmed to be the victims of maltreatment, resulting in 1,990 child fatalities (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). 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. (Eckenrode, Laird and Doris, 1993; 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).

Effective CPS policy responses to shocks that increase child maltreatment risk are essential for safeguarding vulnerable children from severe harm and ensuring the efficiency of the child welfare system. A critical policy objective of CPS is to protect children from maltreatment risk at home by placing at-risk children in foster care. When child maltreatment reports are made, CPS investigates screened-in allegations and makes consequential decisions regarding the placement of children in foster care based on the severity of each case. 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. This diversion may increase investigators' workloads and place additional strain on the system.

This paper examines foster care decisions of CPS in response to the increased child maltreatment risk induced by a massive nationwide opioid supply disruption. Specifically, I investigate changes in prediction mistakes of CPS placement decisions following the increased maltreatment risk triggered by the reformulation of OxyContin in 2010. 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.

Parental substance abuse is one of the leading causes of child maltreatment. In 2020, nearly 60% of caregivers with Medicaid in Florida and Kentucky, whose children were referred to child protective services, had a diagnosis of either a mental health condition or a substance use disorder (Mark et al., 2024). In addition, a recent study shows that even among maltreatment referrals that do not include allegations related to parental substance use, nearly half of the mothers have a history of substance abuse, with opioids being the most common substance (Font and Goldstein, 2024). The role of parental substance abuse as a primary driver of child maltreatment is especially concerning in light of the opioid epidemic, which has claimed roughly as many lives as the number of U.S. soldiers lost in World War II (DeBruyne and Leland, 2015).

The reformulation of OxyContin was a nationwide supply-side 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. It was one of the most significant disruptions in the supply of abusable prescription opioids in U.S. history. Existing economic literature has documented the unintended consequences of the reformulation of OxyContin, such as increased use of substitute drugs (Alpert, Powell and Pacula, 2018; Beheshti, 2019; Evans, Lieber and Power, 2019). The nationwide intervention induced individuals who were heavily dependent on OxyContin to turn to more potent illicit substances, including heroin.

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. I present two main sets of results. First, both event-study and difference-in-differences (DID) specifications indicate that 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. Moreover, I find 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 the fact that the rate of false negatives—cases where children were not initially placed in foster care but were subsequently maltreated—increased significantly 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 may have been neglected by CPS.

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 responds to a nationwide shock that increases maltreatment risk. This gap in the literature is policy-relevant because large-scale shocks to child maltreatment risk are not rare; 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). Each of these crises can disrupt family stability, placing additional strain on the child welfare system. This paper provides insights into how systemic shocks impact CPS responsiveness, highlighting the need for adaptable child welfare policies that can effectively protect children in times of crisis.

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) found that maltreatment allegations increased following the reformulation of OxyContin and the implementation of mandatory prescription drug monitoring programs (PDMPs), suggesting that more children were exposed to maltreatment risk at home following these interventions. On the other hand, Gihleb, Giuntella and Zhang (2022) documented either insignificant changes or a decrease in 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. In particular, I present a channel through which the opioid epidemic may have long-lasting intergenerational effects. 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 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.

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 (Children's Bureau, 2022). It is estimated that one in every eight children in the United States, or about 8.7 million, reside with at least one parent who misuses alcohol or other substances (Lipari and Van Horn, 2017). Parental substance abuse significantly affects the well-being of children. In addition to impairing the ability to care for children, it is also associated with 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). Parental substance abuse as a primary driver of child maltreatment suggests that the risk of maltreatment may have risen significantly since the opioid epidemic, the worst drug crisis in U.S. history.

2.B 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).

Many hypotheses have been proposed to explain the initial factors that triggered the opioid epidemic. Case and Deaton (2015, 2017) propose that demand factors were significant, with deteriorating cultural and economic circumstances potentially leading to an increase in suicides, deaths related to alcohol, and drug overdoses. Other hypotheses examine the influence of supply-side factors. 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 (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. Since its launch in 1996, OxyContin has become one of the most commercially successful drugs ever, with global sales reaching $35 billion.[1] 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 potential primary cause of the opioid epidemic (Alpert et al., 2022; Arteaga and Barone, 2022).

2.C Reformulation of OxyContin

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. The reformulation of OxyContin marks one of the most significant interruptions in the supply of abusable opioids to date. 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). This aligns with several medical studies that have documented that the reformulation achieved its immediate intended effect by reducing opioid abuse (Cicero, Ellis and Surratt,

[1] https://www.latimes.com/projects/la-me-oxycontin-part3/

2012; Butler et al., 2013; Severtson et al., 2013; Havens et al., 2014; Sessler et al., 2014; Cicero and Ellis, 2015; Larochelle et al., 2015; Coplan et al., 2016)

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 deaths related to heroin and synthetic opioids and an increase in cases of Hepatitis and HIV (Alpert, Powell and Pacula, 2018; Beheshti, 2019; Evans, Lieber and Power, 2019). Evans, Harris and Kessler (2022) documented a rise in child maltreatment allegations following the reformulation of OxyContin, which indicates that the intervention impacted parenting behaviors. In the results section below, my first finding aligns with their results, with further heterogeneity analyses corroborating that the increase was driven by the opioid supply disruption. Building upon this "first stage" evidence that the reformulation impacted child maltreatment risk, I examine the foster care decisions made by CPS in response to the policy shock.

3 Conceptual Framework

Before presenting the data and empirical strategy, 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.[2] 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:

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

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

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. Professional reporters are classified as social services, medical, mental health, legal, education personnel, and child daycare providers, while other reporters—such as friends, neighbors, and anonymous reporters—are categorized as non-professionals. 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.

The conventional measure of false negatives may be biased due to two factors associated with the reformulation of OxyContin: occupational and geographic variation in its impacts. Given that the reformulation primarily affected individuals dependent on opioids, workers in occupations with lower average rates of substance use disorders were likely less impacted. 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 professional reporters likely maintained more consistent reporting standards following OxyContin's reformulation, unlike non-professionals. Second, the opioid epidemic has been geographically concentrated in counties with higher rates of poverty, unemployment, disability, lack of college education, reliance on public assistance, divorce, and single-parent households (Monnat, 2018, 2019; Monnat et al., 2019). Reports from non-professionals, such as nearby neighbors, may therefore be more biased than reports from professionals, who are less likely to reside in these communities. In the appendix, I show the robustness of the results to alternative measures of false negatives, where subsequent substantiation and foster care placements following the reports from professionals are used as proxies for subsequent maltreatment.

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 child protective services (CPS) agencies 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.[3] 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.[4] 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 $t \in \{2004, \cdots 2015\}$.[5] 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 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).[6] 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

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

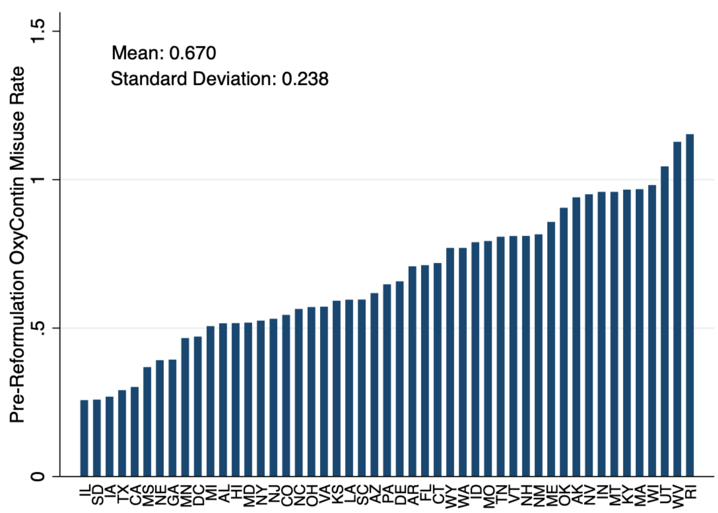
[4] The analysis period of this paper covers 2004-2016. I use the report year rather than the submission year of each allegation because the former represents when the agency was notified of the case. Since report years and submission years do not always align, I include some waves of the NCANDS Child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

[5] 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.

[6] 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.

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.

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 outcomes of interest are maltreatment allegations reported by professionals per 1,000 children and false negatives per 1,000 children and per 1,000 allegations. As discussed in the previous section, I focus on professional allegations because professionals are less likely to be affected by the reformulation of OxyContin in their reporting standards. Table 1 presents the mean values for the pre-reformulation period, 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.

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.

Compared to the low-exposure states, high-exposure states have populations that are more White, less Black, and older.

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 Baltik 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 estimates which identify the differences in the outcomes across states with higher and lower pre-reformulation OxyContin misuse rates in each year relative to 2010.

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. These variables identify the differences across states with higher and lower pre-reformulation OxyContin misuse rates in the pre-reformulation period, short-run and medium-run following the reformulation.

The identification strategy builds upon two assumptions: pre-reformulation OxyContin misuse rate is (1) correlated with the reduction in the OxyContin misuse rate following 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.

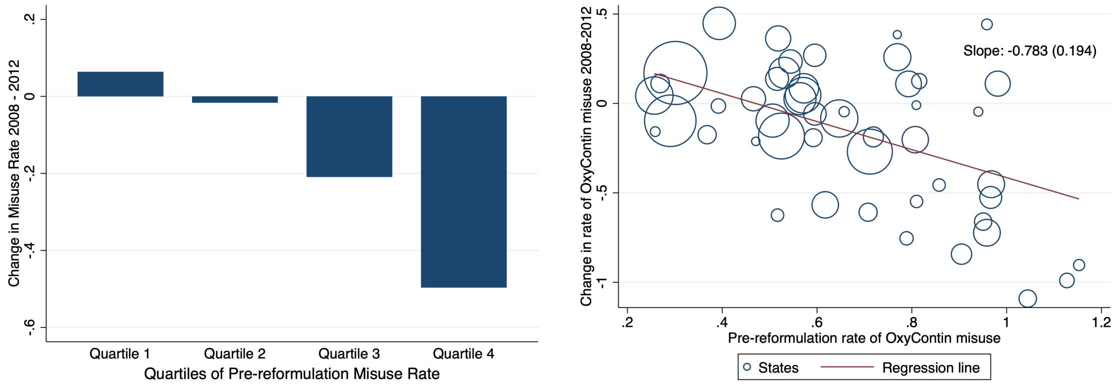
The second assumption requires that the "shares" (or pre-reformulation OxyContin misuse rates) are exogenous to *changes*, as opposed to *levels* of the outcome variables (Goldsmith-Pinkham, Sorkin and Swift, 2020). Empirically, one can assess the plausibility of this assumption by performing pretrends 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 Preminiminary 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 2: Pre-reformulation Rate of OxyContin Misuse and Change between 2008-2012



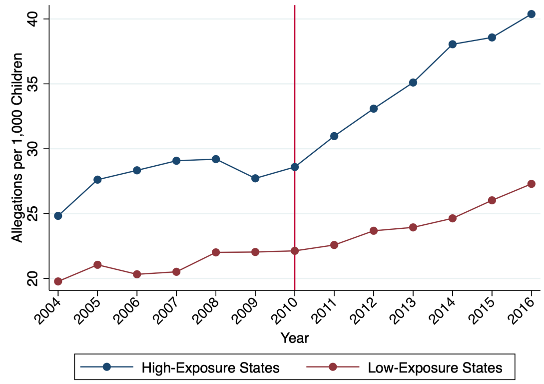
(a) Change Rates by Quartile

(b) Weighted Least Squares

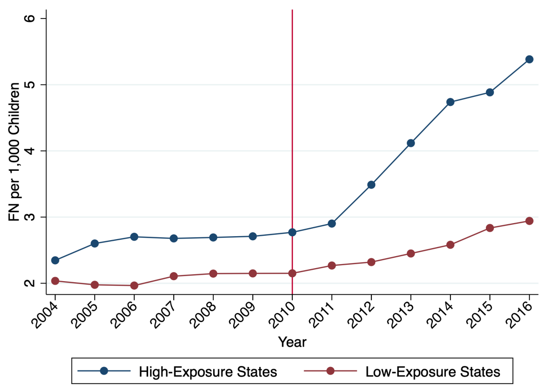
Notes. This figure plots the relationship between pre-reformulation rate of OxyContin misuse and change between 2008 and 2012. Figure (a) plots the changes in the rate of OxyContin misuse from 2008 to 2012 against the quartiles of pre-reformulation rate of OxyContin misuse. Figure (b) plots the weighted 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.

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.

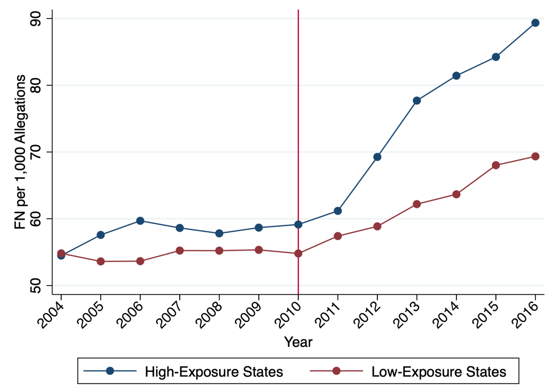
Figure 3: Trends in Maltreatment Allegations and False Nagatives



(a) Allegations per 1,000 Children



(b) False Negatives per 1,000 Children



(c) False Negatives per 1,000 Allegations

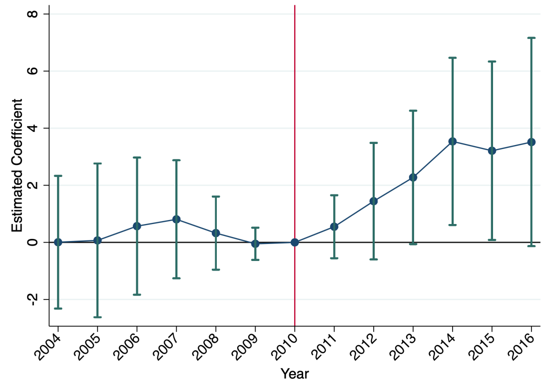
Notes. This figure illustrates the trends in maltreatment allegations reported by professionals per 1,000 children and false negatives per 1,000 children and allegations from 2004 to 2016 separately for states with a pre-reformulation OxyContin misuse rate above or below and equal to the sample mean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

6.B Main Results

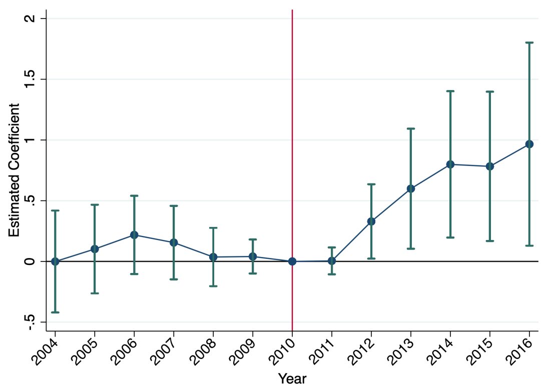
Figure 4 and Table 2 show the event study and difference-in-differences results for the allegations reported by professionals per 1,000 children, and false negatives per 1,000 allegations and children. The allegations reported by professionals increased following the reformulation. A one standard deviation 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. I also report the results on substantiated allegations in Figure A1 and Table A2 which suggest that substantiated physical abuse and neglect reported by professionals increased following the reformulation. However, the results for substantiation should be interpreted with caution, as existing research indicates that, unlike foster care placements, substantiations are strongly influenced by agency-specific factors such as constraints on service accessibility (Font and Maguire-Jack, 2015). Physical abuse reported by non-professionals also increased as reported in Figure A5 and Table A6.

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 A10, A9 and Tables A10, A9 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.

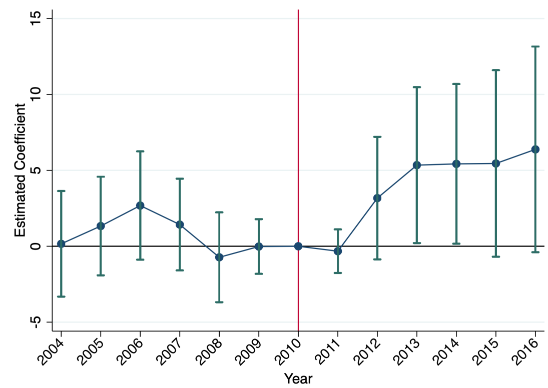
Figure 4: Event Study Results for Allegations and False Negatives



(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.

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

	(1) Allegations	(2) FN per 1,000 Children	(3) FN 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.C Heterogeneity Analysis

Table A3 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 reports, accounting for 51% of all allegations. Among reports made by professionals, these groups represent 91% of the total.

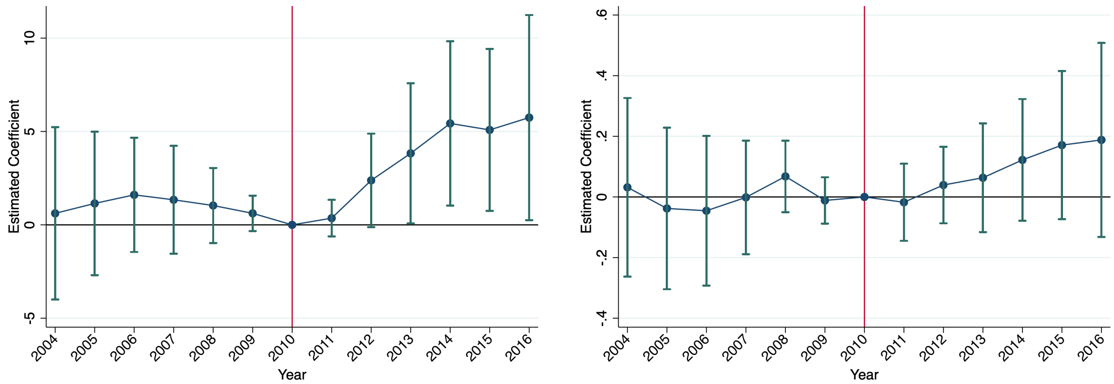
Table A5 and Figure A4 present the results for allegations by child characteristics: race, gender, and age. The results indicate that the effects of the reformulation were heterogeneous across racial groups, with maltreatment allegations for White children increasing at a rate approximately 2.3 times 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 A4, Figure A2 and Figure A3 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 A8, Table A7, Figure A6 and Figure A7 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.

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 A11. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

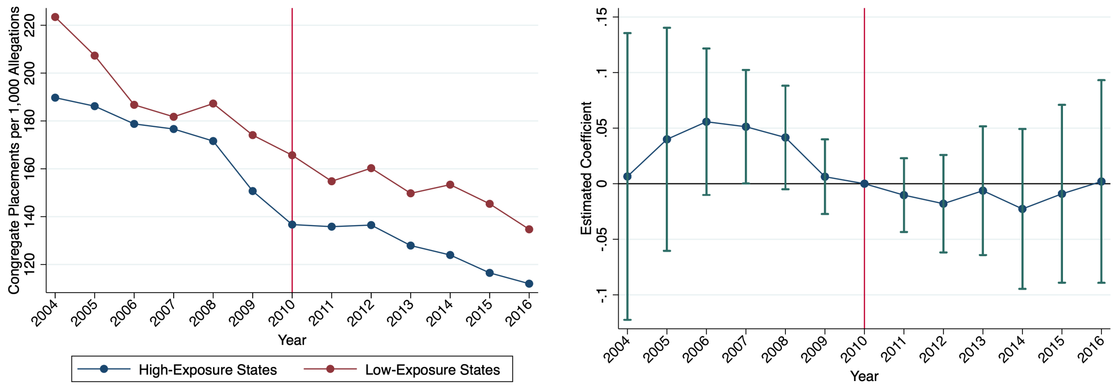
placement rates are statistically significant at the 10 percent level are neglect and physical abuse in the medium-run.

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. Raw trends and event study plot in Figure 6 demonstrate 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



(a) Trends

(b) Event Study

Notes. Figure (a) shows trends in congregate placements per 1,000 foster care placements from 2004 to 2016 for high- and low-exposure states. Figure (b) 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.

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 risk significantly increased following the reformulation of OxyContin, consistent with previous studies that document the unintended consequences of supply-side drug interventions amid the opioid epidemic. Second, more at-risk children were left at home following the intervention. The analysis further suggests that the rise in false negatives is likely driven by an inadequate increase in foster care placement rates relative to the rise in maltreatment risk.

This paper has two main policy implications, one for child welfare policy and one for drug policy. First, in light of the Family First Prevention Services Act of 2018, which places emphasis on prevention services in the national child welfare policy, this paper presents a new perspective that emphasizes the importance of placing at-risk children in foster care. Failure to remove maltreated children from their homes may result in further harmful experiences and re-referrals to CPS. Along with a body of recent literature documenting the positive effects of foster care placements on children's long-term outcomes, the results of this paper suggest the importance of responsive foster care placement policies when more children are exposed to maltreatment risk in their homes. Second, when designing a supply-side drug policy, policymakers should consider the impacts of the policy on children, which will be mediated through the impacts on their parents. In the presence of substitutes, a supply disruption in abusable and highly addictive drugs impacts parental abilities to care for their children as parents could substitute towards more severe drugs, suffer withdrawals, and prioritize drug procurement over childcare.

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Online Appendix

Child Protection in Crisis: Examining Foster Care Decisions Following the Opioid Supply Disruption

Jeongsoo Suh

A First Stage Regression

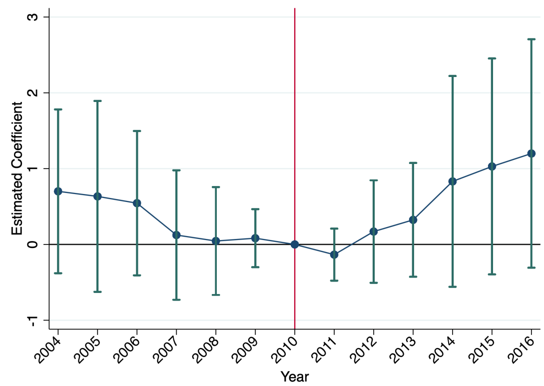
Table A1: First Stage Regressions

	(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

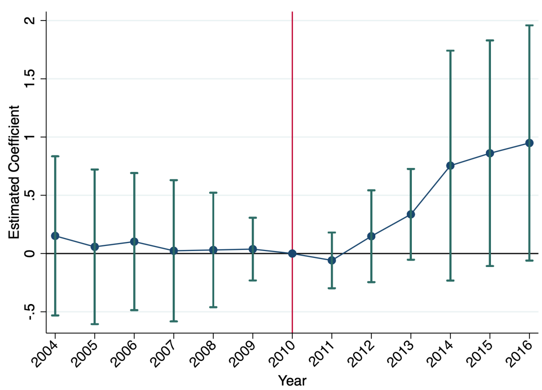
Notes. This table presents point estimates and standard errors from weighted least squares (WLS) regressions of the change in OxyContin misuse rates from 2008 to 2012 on the pre-reformulation rates of OxyContin misuse. Regressions are weighted by child population. Standard errors in parentheses are clustered 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 Substantiated Allegations

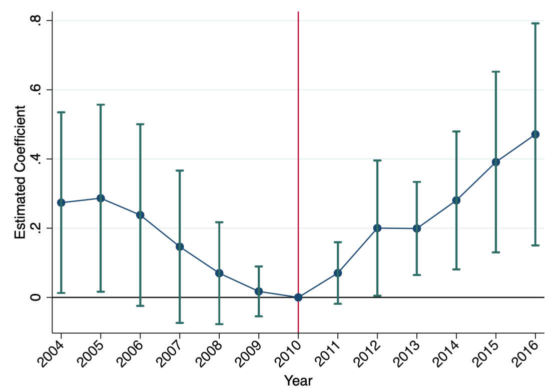
Figure A1: Substantiated Allegations Reported by Professionals



(a) All Types



(b) Neglect



(c) 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 substantiated allegations per 1,000 children reported by professionals. Regressions are weighted by child population.

Table A2: Substantiated Allegations Reported by Professionals

	(1) All Types	(2) Neglect	(3) Physical
Pre-reformulation	0.319	0.064	0.157*
	(0.327)	(0.236)	(0.086)
Short-run	0.119	0.135	0.157**
	(0.276)	(0.146)	(0.067)
	[1.7%]	[2.9%]	[10.1%]
Medium-run	1.014	0.835*	0.378***
	(0.700)	(0.480)	(0.125)
	[14.3%]	[18.1%]	[24.4%]
Mean (2010)	7.072	4.615	1.551
R-squared	0.841	0.882	0.799
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 substantiated allegations per 1,000 children reported by professionals. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Supplemental Summary Statistics

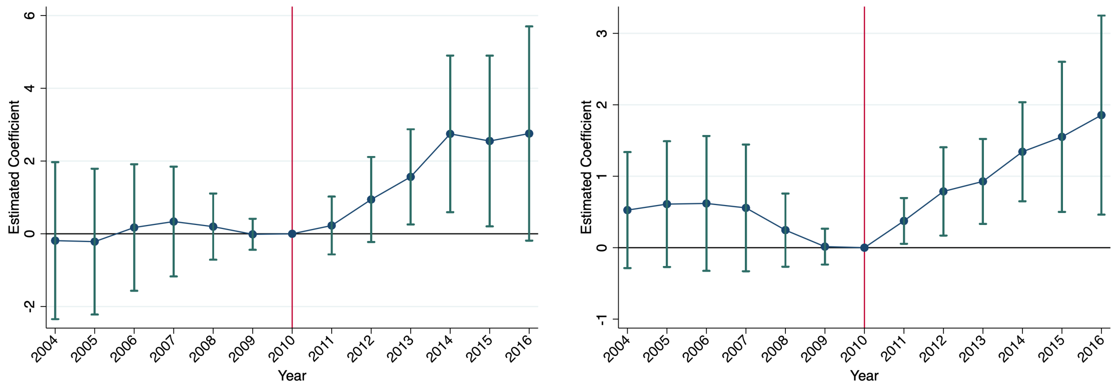
Table A3: Summary Statistics for Maltreatment Allegations

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.

D Allegations by Maltreatment Types and Report Sources

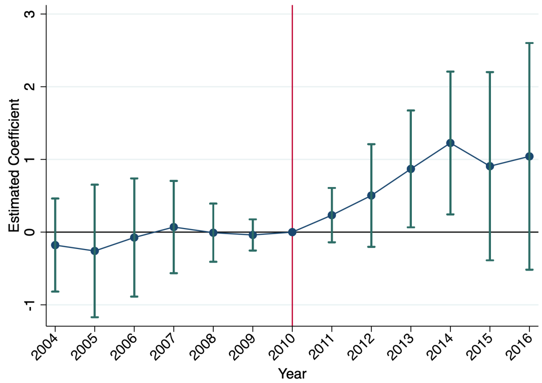
Figure A2: Allegations Reported by Professionals by Maltreatment Types



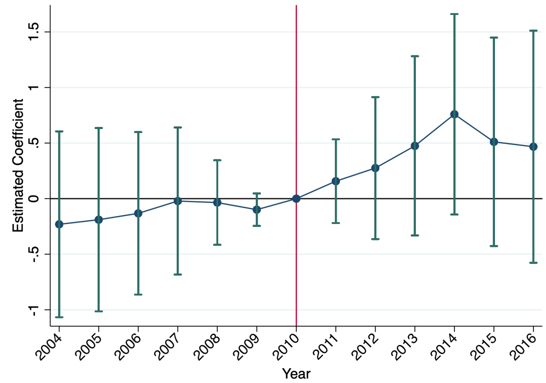
(a) Neglect (b) Physical Abuse

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.

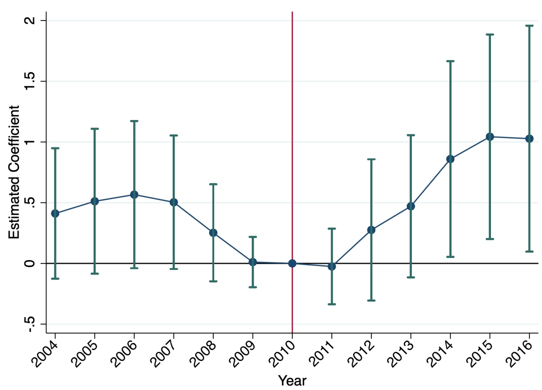
Figure A3: Maltreatment Allegations by Occupation



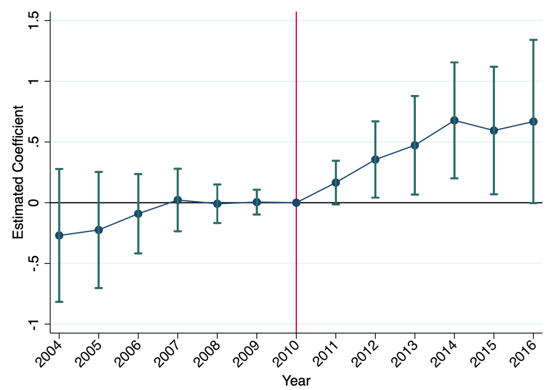
(a) Education Personnel



(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.

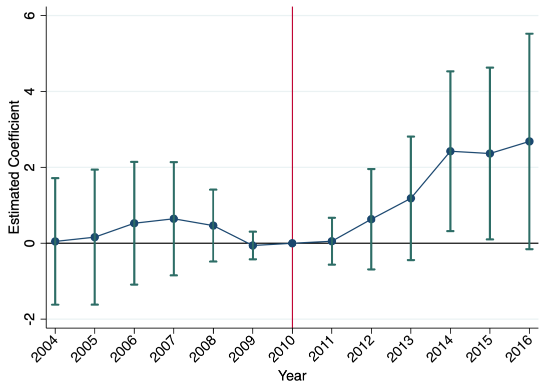
Table A4: Allegations by Maltreatment Type and Report Source

	(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

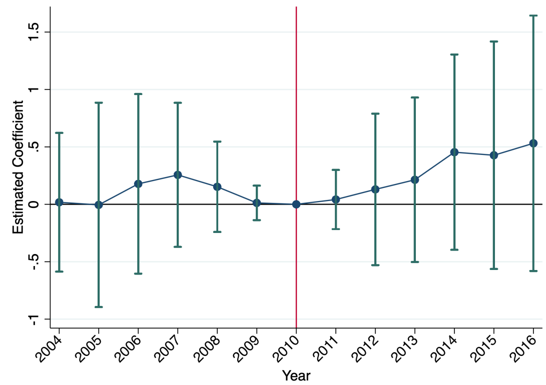
Notes. This table reports point estimates and standard errors from Equation 2, where dependent variables are maltreatment allegations reported by professionals per 1,000 children, broken down by report type and source. Regressions are weighted by child population. Percentage changes from the baseline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

E Allegations by Child Charateristics

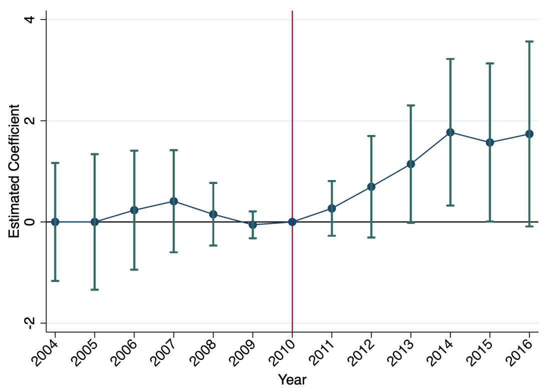
Figure A4: Maltreatment Allegations by Child Characteristics



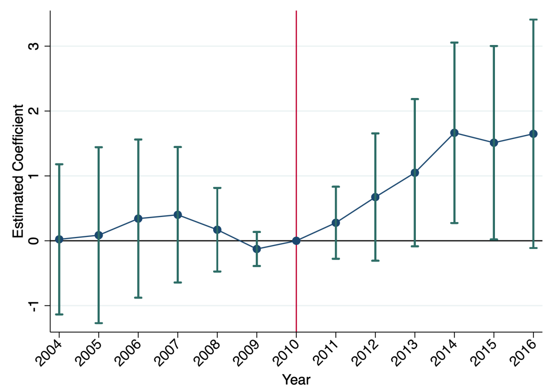
(a) White



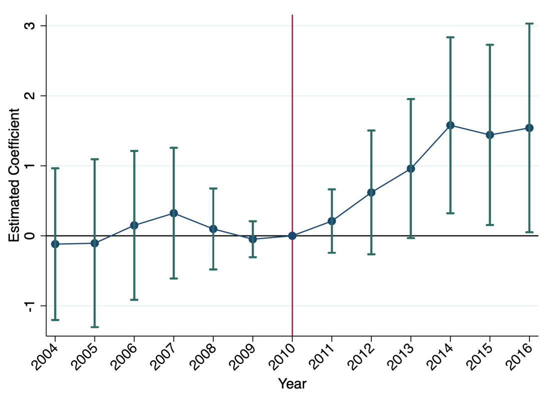
(b) Black



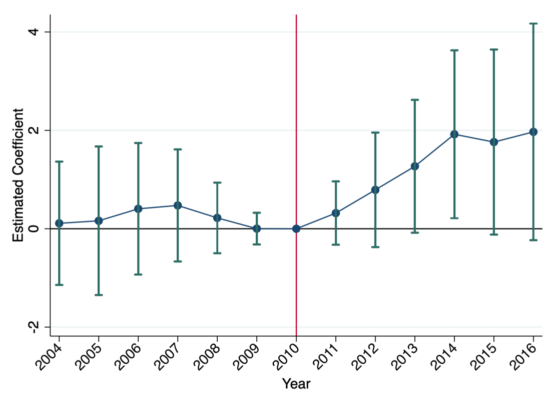
(c) Male



(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.

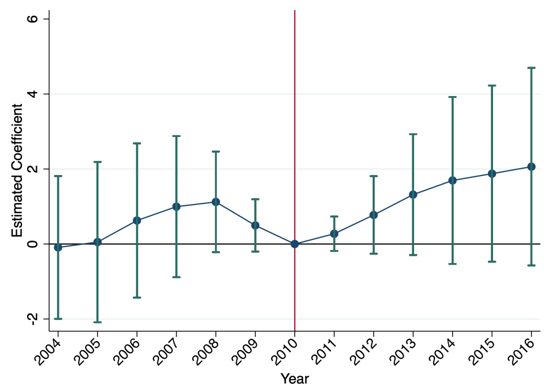
Table A5: Maltreatment Allegations by Child Characteristics

	(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

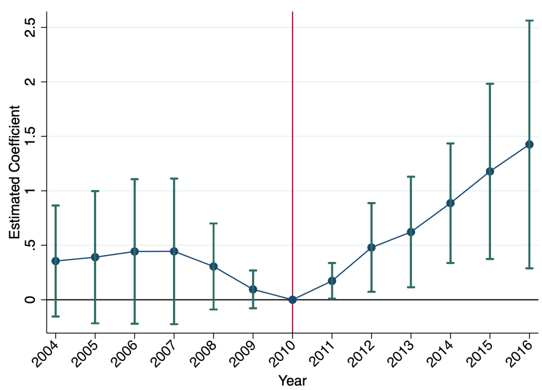
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are maltreatment allegations reported by professionals, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the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

F Allegations by Non-Professionals

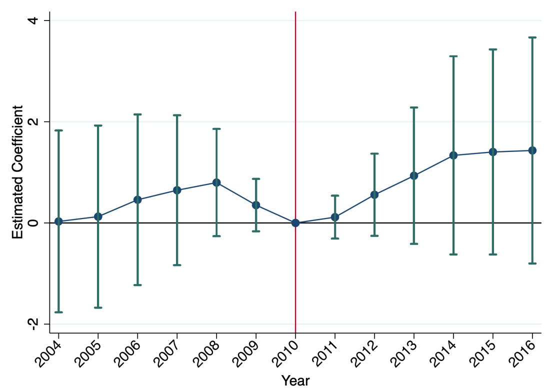
Figure A5: Maltreatment Allegations Reported by Non-Professionals



(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 A6: Maltreatment Allegations Reported by Non-Professionals

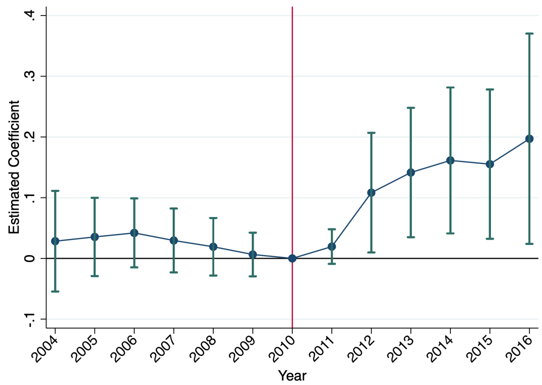
	(1) All Types	(2) Neglect	(3) Physical
Pre-reformulation	0.583	0.432	0.328
	(0.743)	(0.614)	(0.232)
Short-run	0.757*	0.514	0.416**
	(0.431)	(0.337)	(0.168)
	[6.0%]	[5.5%]	[15.9%]
Medium-run	1.781	1.327	1.132***
	(1.142)	(0.989)	(0.385)
	[14.1%]	[14.2%]	[43.1%]
Mean (2010)	12.665	9.342	2.624
R-squared	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.

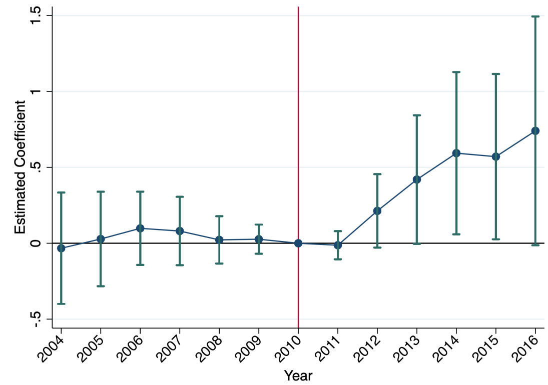
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G False Negatives by Maltreatment Types and Child Charateristics

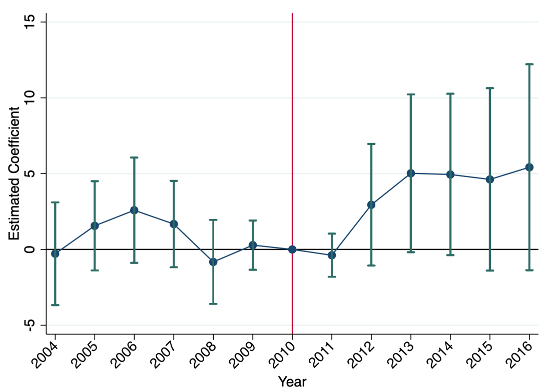
Figure A6: FN per 1,000 Children and Allegations by Maltreatment Types



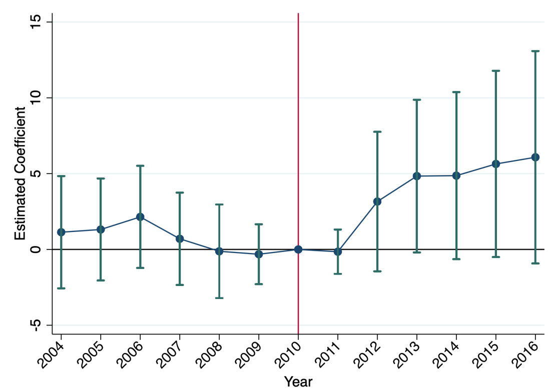
(a) Neglect per 1,000 Children



(b) Physical Abuse per 1,000 Children



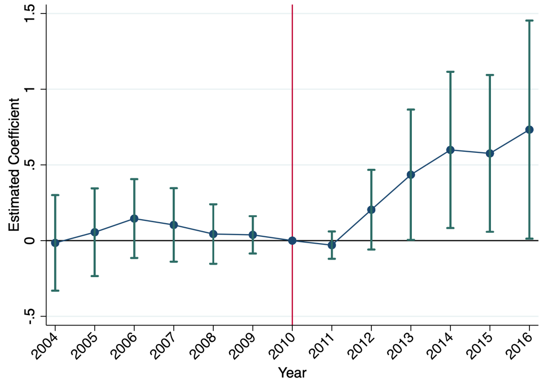
(c) Neglect per 1,000 Allegations



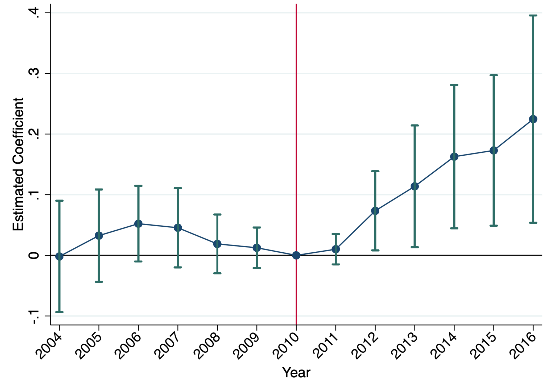
(d) Physical Abuse per 1,000 Allegations

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.

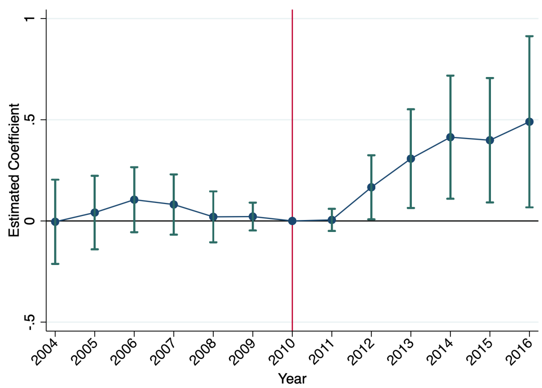
Figure A7: False Negatives per 1,000 Children by Child Characteristics



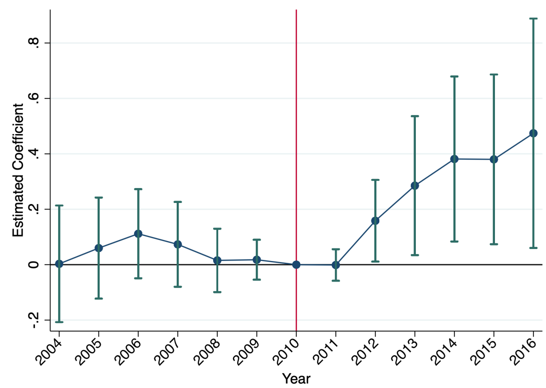
(a) White



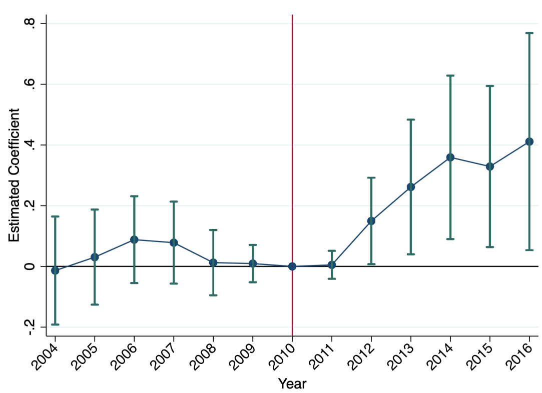
(b) Black



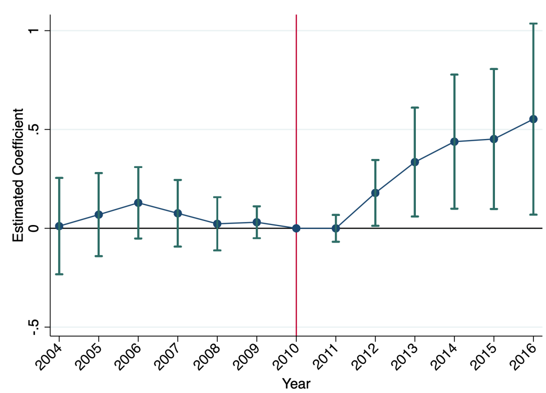
(c) Male



(d) Female



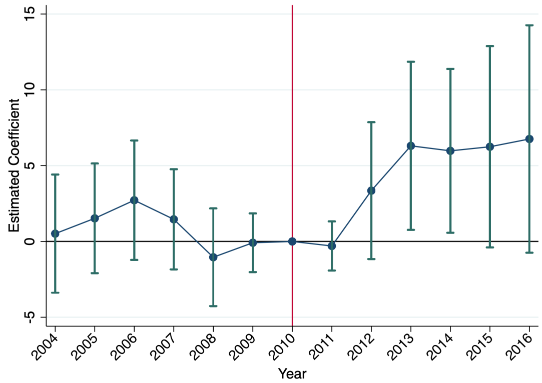
(e) Young



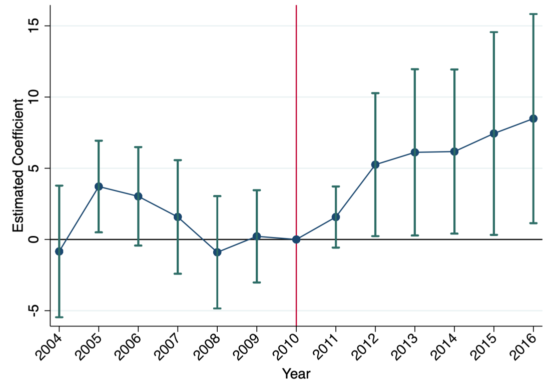
(f) Old

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.

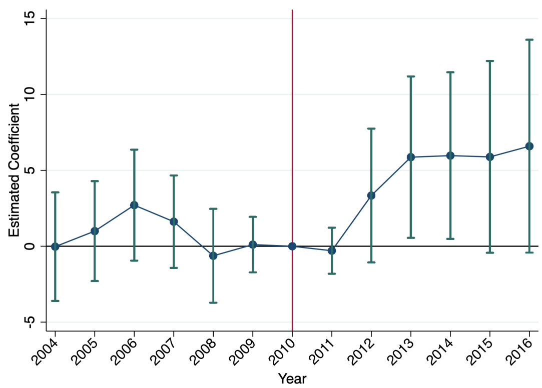
Figure A8: False Negatives per 1,000 Allegations by Child Characteristics



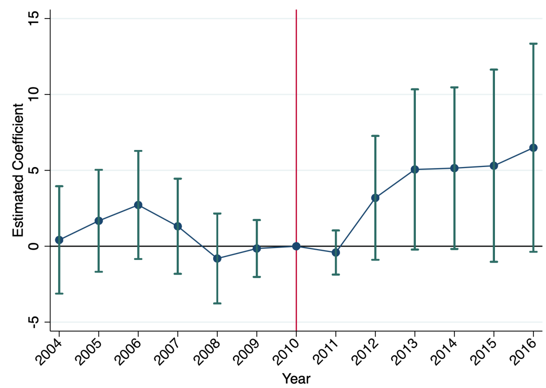
(a) White



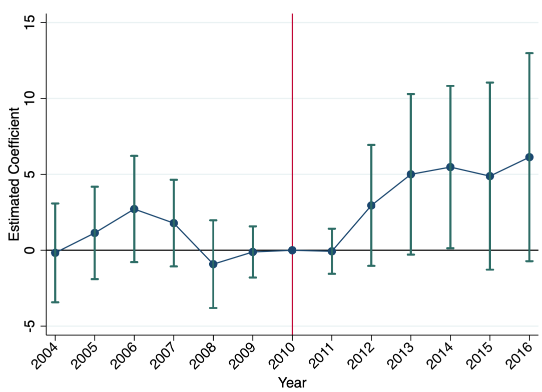
(b) Black



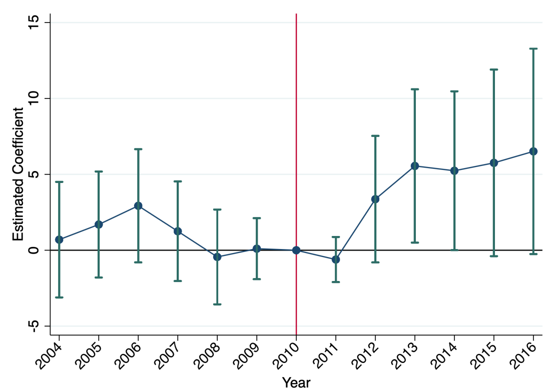
(c) Male



(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 A7: 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.

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

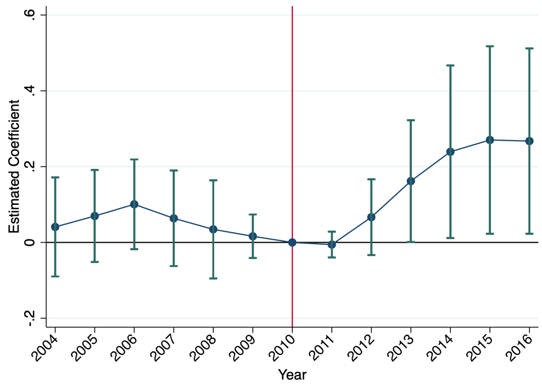
Table A8: FN per 1,000 Allegations by Maltreatment Types and Child Characteristics

	(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

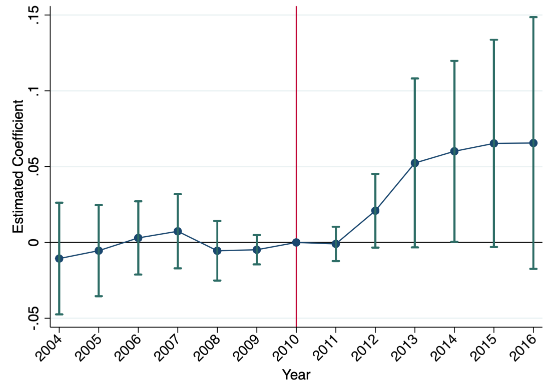
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 allegations by maltreatment types and child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state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

H Alternative Measures of False Negatives

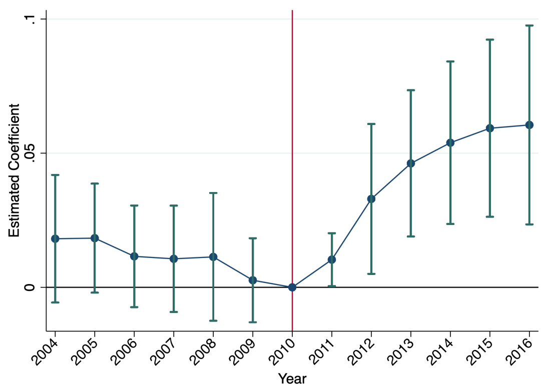
Figure A9: False Negatives per 1,000 Children - Alternative Measures



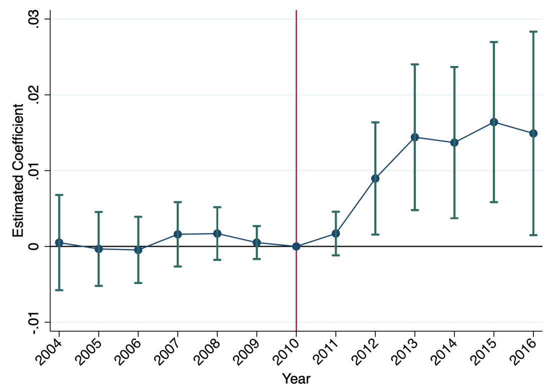
(a) All Types Substantiated



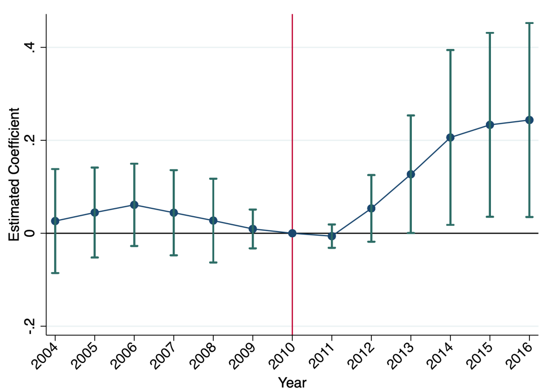
(b) All Types Placed in Foster Care



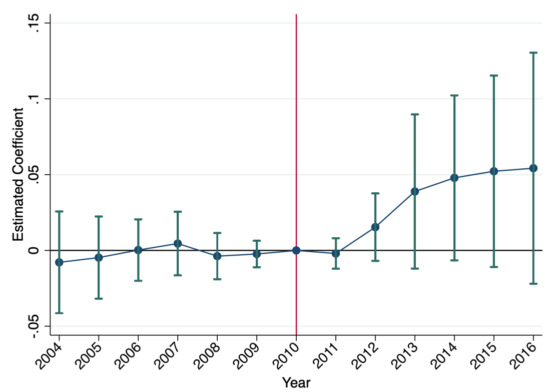
(c) Physical Abuse Substantiated



(d) Physical Abuse Placed in Foster Care



(e) Neglect Substantiated



(f) Neglect Placed in Foster Care

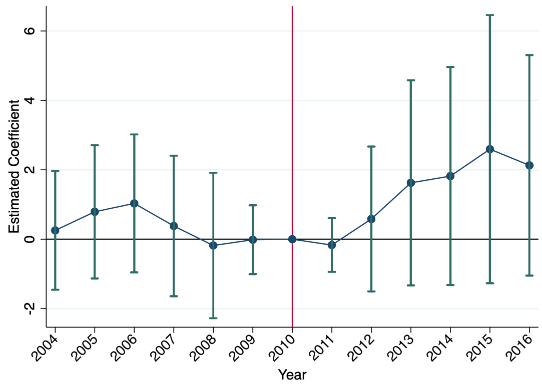
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 children based on alternative measures. Regressions are weighted by child population.

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

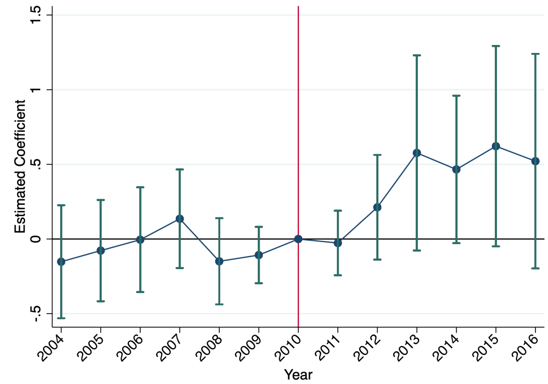
	(1) All Types Substantiated	(2) Neglect Substantiated	(3) Physical Substantiated	(4) All Types Placed	(5) Neglect Placed	(6) Physical Placed
Pre-reformulation	0.050	0.033	0.011	-0.003	-0.002	0.001
	(0.052)	(0.039)	(0.009)	(0.010)	(0.009)	(0.002)
Short-run	0.072	0.056	0.029***	0.023*	0.017	0.008***
	(0.045)	(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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

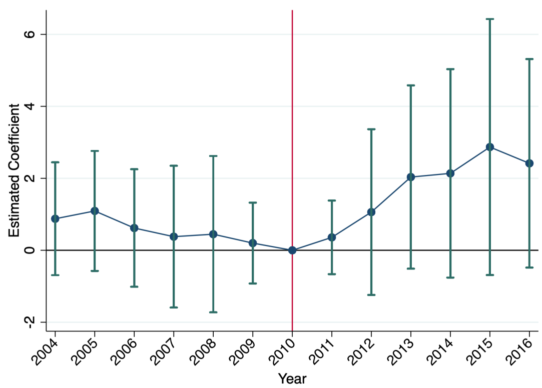
Figure A10: False Negatives per 1,000 Allegations - Alternative Measures



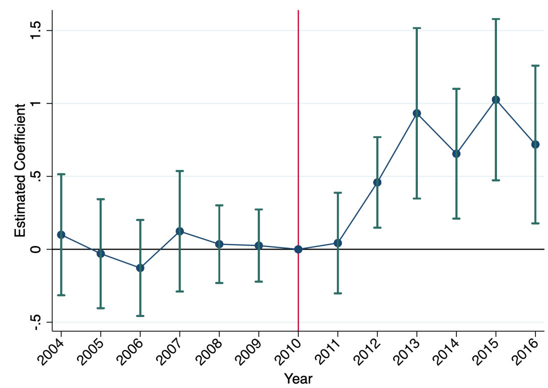
(a) All Types Substantiated



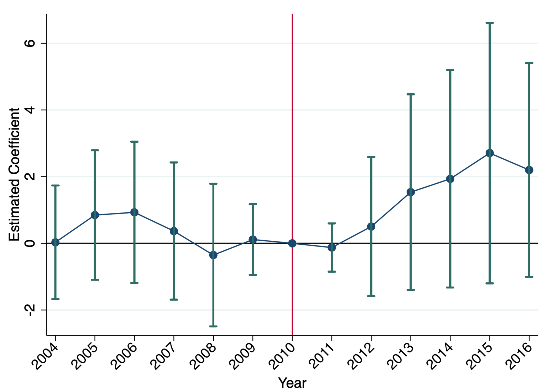
(b) All Types Placed in Foster Care



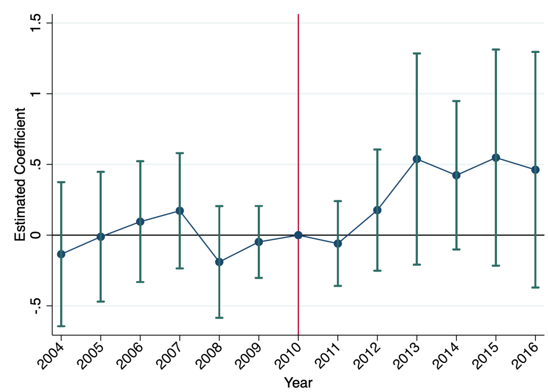
(c) Physical Abuse Substantiated



(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.

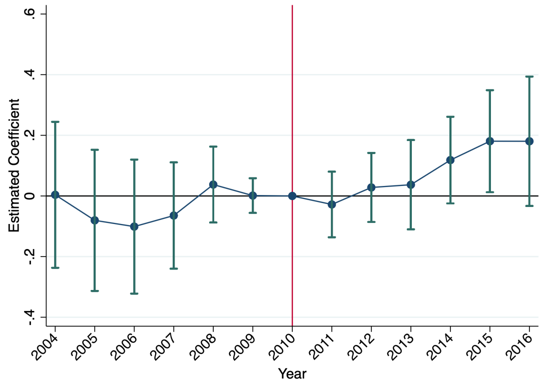
Table A10: False Negatives per 1,000 Allegations - Alternative Measures

	(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

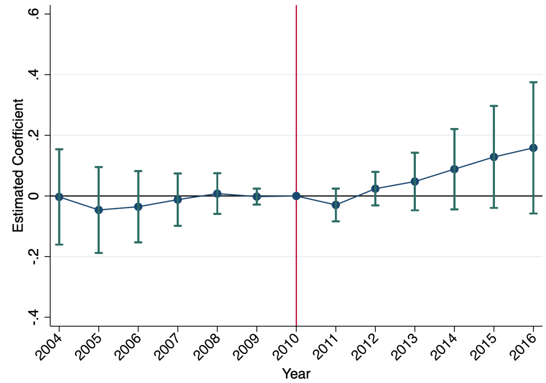
Notes. This table reports point estimates and standard errors from Equation 2, where the dependent variables are false negatives per 1,000 allegations by maltreatment types. Panel A reports estimates based on the following measure for false negatives: a child was initially left at home, subsequently 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I Heterogeneity Analysis for Placement Rates

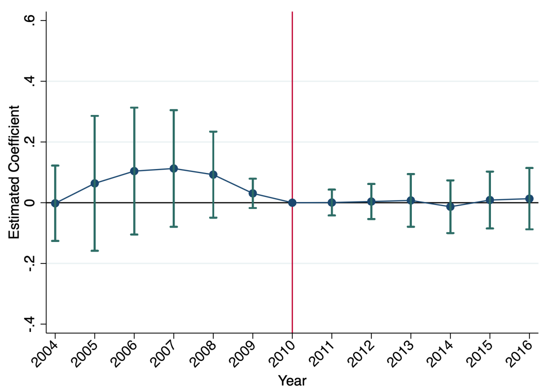
Figure A11: Placements per 1,000 Children by Removal Reason



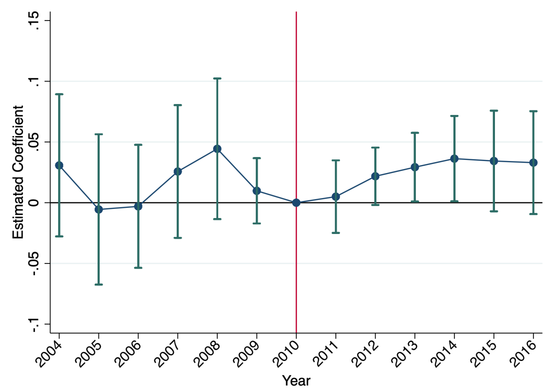
(a) Neglect



(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.

J Policy Variables and Sample Construction

Table A11: 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).