Child Protection in Response to Public Health Crises: Evidence from the Opioid Epidemic

Jeongsoo Suh*

June 8, 2025

(Click here for the latest version)

Abstract

Public health crises have widespread consequences, creating ripple effects across public institutions beyond the health care system. This paper examines the impacts of the opioid epidemic on child maltreatment and how Child Protective Services (CPS) responded to this crisis. To address this question, this study exploits the reformulation of OxyContin, one of the largest opioid supply disruptions in U.S. history that exacerbated the opioid epidemic. Leveraging variation in states' and counties' exposure to the reformulation, I find that the reformulation led to an increase in maltreatment allegations, suggesting a rise in the underlying maltreatment risk and heightened strain on the child welfare system. Moreover, more at-risk children were left in their homes undetected by CPS. This is evidenced by a significant rise in false negatives, cases where children were not initially placed in foster care but were subsequently maltreated. Foster care placement rates remained unchanged, indicating a limited systemic adjustment in response to increased risk. This study underscores the spillover effects of the opioid epidemic on the child welfare system and highlights the need for responsive interventions to protect vulnerable children in times of heightened maltreatment risk.

Keywords: Opioid Epidemic, Child Maltreatment, Foster Care, Child Protective Services
JEL Codes: I12, I18, J13, J18

*Department of Economics, Duke University. Email: jeongsoo.suh@duke.edu.

1 Introduction

Public health crises have widespread consequences, extending beyond the immediate domain of medical care and placing substantial strain on other critical public institutions. For example, the COVID-19 pandemic, HIV/AIDS epidemic, and Ebola outbreaks have not only overwhelmed health care systems but also generated ripple effects that strained social service agencies and disrupted public education systems. Among the most widespread and devastating public health crises is the opioid epidemic, which has claimed the lives of nearly 727,000 people in the United States since 1999 (CDC, 2023) and continues to cause significant social and institutional strain. The unprecedented rise in the opioid overdose deaths prompted the Center for Disease Control and Prevention to declare this the worst drug overdose crisis in U.S. history (Kolodny et al., 2015).

The opioid epidemic has profoundly destabilized families, particularly through its impacts on parents. Substance use significantly impairs parenting abilities, exposing their children to a higher risk of maltreatment (Wells, 2009; Rutherford and Mayes, 2017). Between 2000 and 2019, the fraction of children who entered foster care due to parental drug abuse surged from 15% to 36%.[1] This trend highlights the spillover effects of the opioid epidemic on the child welfare system. The responsive interventions of Child Protective Services (CPS) are critical during periods of heightened maltreatment risk, as the agency can mitigate harm by removing children from risky environments and supporting families in working toward safe conditions, with the ultimate goal of reunification.

This paper examines the impacts of the opioid epidemic on child maltreatment and how CPS responded to this crisis. To address this question, I use the reformulation of OxyContin, a nationwide supply-side drug policy, as a natural experiment that exacerbated the opioid epidemic. This supply disruption, which aimed to reduce OxyContin abuse by introducing an abuse-deterrent version of the original formulation, inadvertently exacerbated the opioid

[1]These are calculated using AFCARS Foster Care Files 2000 and 2019.

epidemic by driving users toward illicit, more addictive and potent substances, resulting in higher rates of opioid overdoses, heroin-related arrests, and homicides.

Leveraging variation in pre-reformulation OxyContin misuse and Schedule II opioid prescriptions across states and counties, I estimate the causal effects of the reformulation of OxyContin on child maltreatment allegations and foster care decisions. These measures capture differential exposure to the reformulation, as states and counties with higher pre-reformulation OxyContin misuse rates and Schedule II prescription opioids per capita experienced greater declines in OxyContin misuse rates following the intervention. I use event study and difference-in-differences frameworks to compare outcomes between regions with higher and lower exposure to the reformulation.

I present three main sets of results. First, states and counties with higher exposure to the reformulation experienced relatively larger increases in maltreatment allegations, primarily driven by reports from professionals including educational, medical, legal, and social services personnel. These findings suggest that the reformulation of OxyContin heightened maltreatment risk by affecting parents through various unintended consequences documented in the literature. Specifically, the rise in opioid overdoses, heroin-related fatalities and crimes associated with procuring illicit drugs, including heroin and synthetic opioids, likely contributed to increased maltreatment risk. In addition, the surge in maltreatment allegations indicates a heavier investigative burden and greater strain on the child welfare system.

Second, I find that the opioid epidemic systematically increased the number of children harmed without adequate institutional intervention. 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 and counties with higher exposure to the reformulation. These results suggest that a significant number of children exposed to maltreatment risk during the opioid epidemic were left at home unprotected. The increase in false negatives per 1,000 allegations, in addition to per 1,000 children, indicates that a growing share of at-risk children systematically went undetected by CPS during this period.

Third, I find that changes in the foster care placement rates were indistinguishable from zero following the reformulation. These results suggest that CPS has operated under a rule-of-thumb placement rule, placing a relatively fixed proportion of allegations in foster care rather than adjusting placement thresholds in response to changes in underlying risk. Combined with a surge in false negative rates, these results point at the limited systemic adjustment in response to increased risk induced by the opioid epidemic.

In addition to these main findings, I provide suggestive evidence that the misalignment between the increased maltreatment risk and CPS placement decisions was not primarily driven by a shortage of foster homes. This is shown by analyzing changes in the rate at which children were placed into congregate care, a setting where multiple children reside together and is generally considered a last resort. The congregate placement rate remained stable before and after the reformulation, providing suggestive evidence that the limited response to heightened risk was not primarily due to capacity constraints.

This paper makes several contributions to the literature. First, it expands the existing research on 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). Regarding the impact on child welfare, there have been seemingly incongruous findings. Evans, Harris and Kessler (2022) documented the rise in maltreatment allegations whereas Gihleb, Giuntella and Zhang (2022) found stagnant or declining foster care placements. The absence of a unifying framework has made it difficult to reconcile these findings. This paper addresses this gap by providing evidence that more at-risk children were left at home during the opioid epidemic, as CPS responses did not fully adjust to the rising severity of maltreatment risk. Furthermore, by examining the impact of the opioid epidemic on child welfare, this paper highlights the potential for the opioid epidemic to generate intergenerational consequences, contributing to long-term declines in mobility and widening socioeconomic inequality.

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 importance of considering policy complementarities and institutional spillovers, where the effectiveness or harm of one intervention depends on the response capacity of other systems (Coe and Snower, 1997; Orszag, 1998; Chang, Kaltani and Loayza, 2009).

Lastly, this paper 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 particularly policy-relevant, as large-scale shocks to child maltreatment risk, such as drug epidemics (Evans, Harris and Kessler, 2022), economic downturns (Brooks-Gunn, Schneider and Waldfogel, 2013), and climate change (Evans, Gazze and Schaller, 2023), are not are. By addressing this gap, the study underscores the need for adaptable child welfare policies capable of protecting vulnerable children during periods of crisis.

2 Background

This section provides background information to contextualize the results presented in section 6. Section 2.A reviews empirical findings on the association between parental substance abuse and child maltreatment. Section 2.B offers an overview of the foster care system in the United States. Section 2.C provides documented facts about the opioid epidemic. Section 2.D discusses how the reformulation of OxyContin intensified the opioid epidemic and contributed to increased child maltreatment risk.

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 increases the stress associated with caregiving (Wells, 2009; 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 et al., 2000).

Since 2005, parental substance abuse has consistently been one of the most prevalent risk factors 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, approximately 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 assessment of the risk. The most significant intervention is the removal of children from their homes and placement into foster care. The primary justification for placing a child in foster care is the potential risk of maltreatment if the child remains at home.[2] This means that CPS is responsible for predicting whether a child would be maltreated if left at home rather than placed in foster care. If CPS concludes that the reported children would be maltreated at home, they 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

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

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

From 1999 to 2022, nearly 727,000 people died from an opioid overdose in the United States (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 worst 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, total 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 increased children's exposure to maltreatment risk at home through multiple channels. First, an increase in the opioid overdose deaths as well as total overdose deaths indicate that more parents were adversely affected by the opioid epidemic. 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 classified as a Schedule I substance under the Controlled Substances Act, making it illegal to purchase and often driving high-risk criminal behaviors to obtain it. Mallatt (2022) and Powell and Pacula (2021) documented an increase in heroin-related arrests following the reformulation, while Park (2022) and Tan (2024) documented a rise in homicide rates, suggesting that expanded illicit market activities led to more crimes. These findings indicate that parents who turned to heroin were more likely engaged in criminal activities, further exposing their children to risk at home.

3 Data

3.A Child Welfare Data

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.[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 2004-2018 and AFCARS Foster Care Files 2004-2018 for the analysis.[4] For the analysis of foster care placements, I exclude six states that did not report placement outcomes in the NCANDS files.[5] 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 $t \in \{2004, \cdots 2015\}$.[6] Additionally, I exclude states that do not report foster care placements. These criteria yield a sample of 38 states and Washington D.C. for the analysis of false negatives.

3.B Construction of Super Counties

One feature of the NCANDS Child Files is that county identifiers are masked for counties with fewer than 700 allegations. Excluding all masked counties from the analysis sample would result in censoring bias. To minimize bias from this censoring, I construct "super counties" within each state using a two-step procedure. First, I identify counties that appear in every year of the Child Files. These are counties with more than 700 allegations annually throughout the sample period. There are 597 such "identified" counties in the data, accounting for approximately 69% of the U.S. population. Second, I create "super counties" in each state by aggregating outcome and control variables across all counties with fewer

[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] These states are Alabama, Georgia, Michigan, North Carolina, New York, and Pennsylvania

[6] 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.

than 700 allegations. This step results in 46 super counties. The final balanced panel for the county-level analysis consists of 597 identified counties and the constructed super counties.

3.C OxyContin and Prescription Opioid Data

The identification strategy in this paper compares outcomes across regions that were more versus less exposed to the OxyContin reformulation. Ideally, exposure would be measured using pre-reformulation OxyContin misuse rates, following the approach in Alpert, Powell and Pacula (2018), since regions with higher misuse rates experienced larger declines in the misuse rates following the reformulation. The underlying idea is that the supply disruption had a greater impact in areas where OxyContin misuse was more prevalent. However, a practical limitation is that data on OxyContin misuse is only available at the state level, offering limited identifying variation. To address this, I complement the state-level analysis by leveraging county-level variation in Schedule II prescription opioids per capita, which is available at the county level, following the approach in Evans, Harris and Kessler (2022). Schedule II opioids, which include oxycodone, are highly addictive and subject to the most stringent federal regulations.

For the state-level analysis, I utilize the measures for nonmedical OxyContin, 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). 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. This data is only available at the state level, not at the county level. 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).

For the county-level analysis, I use Schedule II prescription opioid data from the Centers for Disease Control and Prevention (CDC), covering the period from 2006 to 2009.[7] This data includes nearly 85% of all retail pharmacy providers in the United States, excluding hospitals. The pre-reformulation exposure measure is calculated as the population-weighted mean number of all Schedule II opioid prescriptions per capita in each county for the period 2006 to 2009.

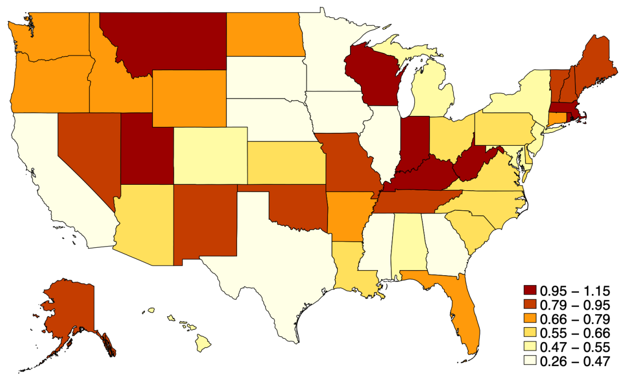
3.D Descriptive Statistics

Figure 1 shows the geographic distribution of the pre-reformulation OxyContin misuse rate by state and Schedule II prescription opioids per capita by identified county. The gray areas in Figure (b) represent super counties, where the exposure measure is computed by taking the population-weighted average of the number of Schedule II prescription opioids across masked counties. These figures illustrate significant variation in the exposure measure at both the state and county levels.

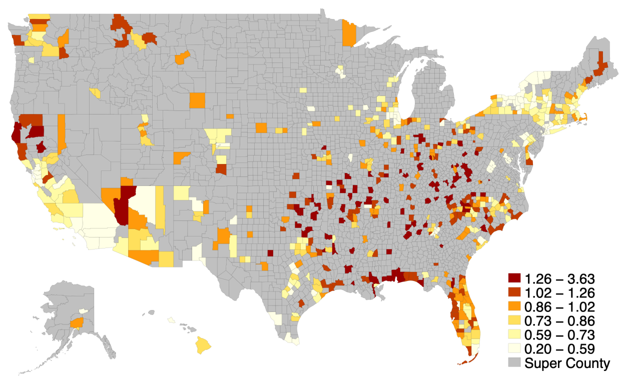
The main outcomes of interest are maltreatment allegations per 1,000 children, and false negatives measured both per 1,000 children and per 1,000 allegations. CPS follows clear guidelines, placing children in foster care only when there is a potential risk of maltreatment if they remain at home. Under this framework, CPS assesses the risk of subsequent maltreatment and predicts the likelihood of harm if a child is left at home. False negatives occur when CPS mistakenly leaves a child at home following an investigation, but the child is re-reported within six months. These are formally defined using the potential outcomes framework in section 4, and alternative proxies for subsequent maltreatment are used to test the robustness of the results in section 6.D.

[7] While covering the period from 2004 would be ideal for consistency with the state-level analysis, which enables a more robust test of pretrends, the earliest available data from the CDC is from 2006. The same years of data were used in Evans, Harris and Kessler (2022)

Figure 1: Exposure Measure by State and Identified County



(a) State



(b) Identified County

Notes. This figure illustrates the measure of exposure to the reformulation of OxyContin by state and identified counties. Figure (a) shows the rate of nonmedical use of OxyContin between 2004 and 2009 across states. Figure (b) shows Schedule II opioid prescriptions per capita across 597 identified counties between 2006 and 2009, where counties with less than 700 allegations in each state are classified as super counties.

False negatives measured per 1,000 children and per 1,000 allegations each offer distinct and complementary insights. False negatives per 1,000 children reflect how many at-risk children in the population were missed by the system, providing a direct measure of the broader welfare impact on the child population. This measure is relevant for estimating the overall impact of the opioid epidemic on child well-being at the population level. However, it speaks less directly to CPS responses, as CPS only observes and makes decisions about reported children, not the entire population. This is captured by false negatives per 1,000 allegations which reflect how CPS handled the cases it observed in response to the opioid epidemic.

Professional reporters include social services, medical, mental health, legal, education personnel, and child daycare providers. As shown in Table A2, allegations from professionals account for approximately 56% of all allegations, whereas allegations from non-professionals account for 20%. The rest of the allegations have unknown or anonymous reporters. I focus on allegations reported by professionals, as they are more 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 including neighbors, friends, and relatives, for two reasons. First, studies show significant variation in the rates of substance use disorders (SUD) across occupations, with professionals, as classified above, having the lowest rates 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 should have enabled them to maintain greater consistency in reporting standards during periods of crisis compared to non-professionals.

Table 1: Summary Statistics

	Pre-reformulation			Post-reformulation		
	Low-exposure	High-exposure	p-value	Low-exposure	High-exposure	p-value
Panel A: States						
Allegations per 1K Children	20.908	28.263	0.108	24.360	35.523	0.014
False Negatives per 1K Children	2.060	2.639	0.083	2.529	4.065	0.010
False Negatives per 1K Allegations	53.752	59.177	0.200	60.626	74.360	0.017
Percent White	76.911	84.372	0.000	75.247	82.729	0.001
Percent Black	14.526	9.582	0.054	14.724	10.061	0.079
Percent Hispanic	17.133	10.671	0.201	19.122	12.608	0.226
Percent female	50.876	50.826	0.803	50.826	50.759	0.727
Percent age 0 to 19	27.900	26.720	0.094	26.501	25.342	0.174
Percent age 20 to 24	7.065	6.918	0.344	7.159	6.970	0.168
Percent age 25 to 34	13.471	12.763	0.027	13.754	13.103	0.032
Percent age 35 to 44	14.417	14.025	0.032	12.972	12.500	0.009
Percent age 45 to 54	14.427	14.632	0.383	13.869	13.919	0.819
Percent age 55 to 64	10.598	11.289	0.009	12.236	12.834	0.044
Percent over age 64	12.101	13.652	0.068	13.608	15.332	0.055
Unemployment rate	6.014	5.437	0.062	7.313	6.900	0.337
Labor force participation rate	66.077	65.603	0.640	63.630	62.959	0.499
Panel B: Counties						
Allegations per 1K Children	22.865	28.629	0.054	24.190	35.401	0.002
False Negatives per 1K Children	2.323	2.656	0.291	2.729	3.819	0.045
False Negatives per 1K Allegations	56.168	52.075	0.256	64.233	64.671	0.913
Percent White	77.789	80.909	0.107	76.232	79.812	0.061
Percent Black	12.501	14.360	0.307	12.756	14.598	0.307
Percent Hispanic	19.632	7.534	0.001	21.295	8.701	0.001
Percent female	50.803	50.948	0.310	50.753	50.909	0.227
Percent age 0 to 19	13.110	12.866	0.299	13.045	12.814	0.347
Percent age 20 to 24	3.534	3.417	0.077	3.572	3.503	0.310
Percent age 25 to 34	6.763	6.304	0.004	6.968	6.414	0.000
Percent age 35 to 44	7.145	6.758	0.000	6.536	6.180	0.001
Percent age 45 to 54	7.283	7.309	0.786	6.970	6.875	0.221
Percent age 55 to 64	5.403	5.852	0.001	6.061	6.474	0.003
Percent over age 64	6.081	6.830	0.010	6.759	7.652	0.004
Unemployment rate	5.891	6.644	0.029	7.079	7.576	0.134
Labor force participation rate	64.101	61.118	0.000	62.390	58.497	0.000

Notes. This table presents summary statistics for low- and high-exposure states and counties, separately for the pre-reformulation period (2004–2009 for states and 2006-2009 for counties) and the post-reformulation period (2010–2016). High-exposure states are those with an above-median pre-reformulation OxyContin misuse rate, while high-exposure counties are those with an above-median pre-reformulation prescription opioid supply per capita. The third and sixth columns report p-values from tests for the equality of means.

Table 1 presents summary statistics for low- and high-exposure states and counties, separately for the pre-reformulation period (2004–2009 for states and 2006-2009 for counties) and the post-reformulation period (2010–2016). High-exposure states are those with an above-median pre-reformulation OxyContin misuse rate, while high-exposure counties are those with an above-median pre-reformulation Schedule II prescription opioid supply per capita. The third column reports p-values from tests for the equality of means. Prior to the reformulation, differences in allegations per 1,000 children and false negatives per 1,000 allegations between high- and low-exposure states were statistically insignificant but became significant in the post-reformulation period. Differences in false negatives per 1,000 children were significant in both periods, with a larger magnitude observed after the reformulation. Similar patterns are observed at the county level. Before the reformulation, differences in allegations per 1,000 children and false negatives per 1,000 children and per 1,000 allegations between high- and low-exposure counties were statistically insignificant. After the reformulation, differences in allegations per 1,000 children and false negatives per 1,000 children became statistically significant.

4 Conceptual Framework

In this section, I present a conceptual framework for analyzing CPS responses to a shock that increases child maltreatment risk. Intuitively, such a shock raises the proportion of children who would be maltreated if left in their homes. CPS's response to this shock is reflected in its placement decisions for marginal children who were exposed to maltreatment risk due to the shock, i.e., those who would not have been at risk in its absence. I evaluate CPS responses through prediction mistakes, as CPS placement decisions are made under clear policy guidelines. The primary justification for placing a child in foster care is the potential risk of maltreatment if the child remains at home.[8] This means that CPS is responsible for predicting whether a child would be maltreated if left at home rather than placed in foster care.

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. CPS's response to a shock that exposes children to maltreatment is captured

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

by their placement decisions for those whose Y_i^* switches from 0 to 1 as a result of the shock. A prediction mistake for these children is a false negative which occurs when an at-risk child ($Y_i^* = 1$) is left at home ($D_i = 0$). Formally, this is defined as:

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

The false negative rate can be expressed as follows:

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

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 $\mathbb{P}(Y_i^* = 1)$. CPS response is captured by $\mathbb{P}(D_i = 1|Y_i^* = 1)$, the placement rate for at-risk children. CPS can mitigate the rise in the false negative rate caused by an increase in at-risk children by raising the placement rate for these children. A rise in the false negative rate suggests that some of the children exposed to the risk by the shock were left in their homes.

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 reporters are explained in section 3. 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. In section 6.D, 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.

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' and counties' exposure to the reformulation. For the event study, I estimate the following equations:

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

$$y_{ct} = \sum_{k=2006}^{2016} \gamma_k \mathbb{1}[t = k] \times \text{Exp}_c + \alpha_c + \gamma_t + X'_{ct}\lambda + u_{ct} \tag{2}$$

where y_{st} denotes the outcome in state s and year t and y_{ct} denotes the outcome in county c and year t. α_s and α_c denote state and county fixed effects, and γ_t denotes year fixed effects. Exp_s denotes a standardized pre-reformulation (2004-2010) rate of nonmedical OxyContin use and Exp_c denotes a standardized pre-reformulation (2006-2010) number of Schedule II opioid prescriptions per capita in county c. 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. X_{ct} denotes the same vector at the county level. I normalize the coefficient for year 2010 to zero and cluster standard errors at the state level. The variables of interest are β_t and γ_t terms which identify how the outcomes in state s and county c in year t would have been different had its pre-reformulation OxyContin misuse rate or Schedule II opioid prescriptions per capita been one standard deviation higher.

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

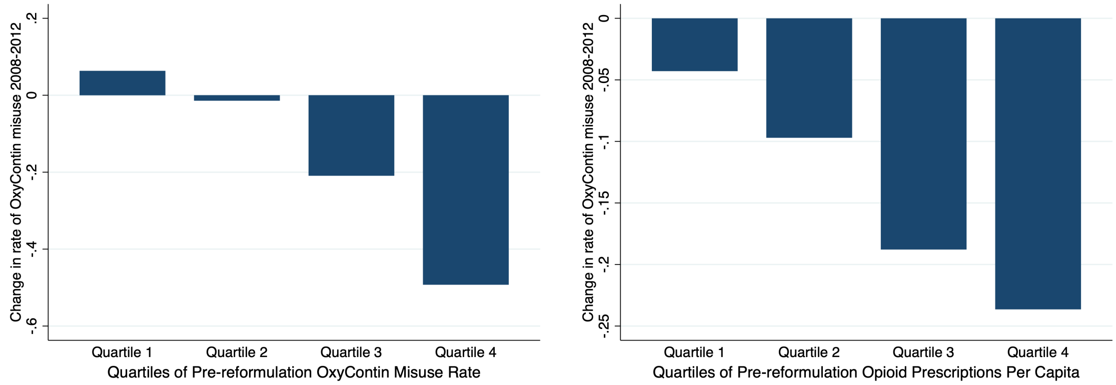
$$y_{st} = \beta_1 \times \text{Pre}_t^s \times \text{Exp}_s + \beta_2 \times \text{SRpost}_t \times \text{Exp}_s + \beta_3 \times \text{MRpost}_t \times \text{Exp}_s + \alpha_s + \gamma_t + X'_{st}\lambda + \epsilon_{st} \tag{3}$$

$$y_{ct} = \gamma_1 \times \text{Pre}_t^c \times \text{Exp}_c + \gamma_2 \times \text{SRpost}_t \times \text{Exp}_c + \gamma_3 \times \text{MRpost}_t \times \text{Exp}_c + \alpha_c + \gamma_t + X'_{ct}\lambda + u_{ct} \tag{4}$$

where Pre_t^s and Pre_t^c take a value of 1 for years from 2004 to 2009 and 2006 to 2009, respectively. 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. Standard errors are clustered at the state level. The variables of interest are $\beta_1, \beta_2, \beta_3, \gamma_1, \gamma_2$ and γ_3 terms which identify how the outcomes in state s and county c in year t would have been different in the pre-reformulation period, short-run and medium-rum following the reformulation had its pre-reformulation OxyContin misuse rate or Schedule II opioid prescriptions per capita been one standard deviation higher. The effects are expected to be larger in the medium run, as existing literature on the consequences of the reformulation, including overdose deaths from opioids and heroin, as well as homicide rates, shows that these impacts tend to intensify over time. This is primarily because it takes time for the illicit drug market to evolve and for the resulting effects to manifest.

The identification strategy builds upon two assumptions: pre-reformulation OxyContin misuse rate and Schedule II opioid prescriptions per capita are (1) correlated with the exposure to the reformulation and (2) are not correlated with factors that could affect the differential trends in the outcomes after the reformulation, in the absence of the reformulation. Figure 2 presents the "first-stage" results, where Figure (a) plots the change in OxyContin misuse rates against quartiles of states' pre-reformulation OxyContin misuse rates and Figure (b) plots the change in OxyContin misuse rates against quartiles of counties' pre-reformulation Schedule II opioid prescriptions per capita. Both plots suggest that states

Figure 2: Exposure Measures and Change in OxyContin Misuse Rate between 2008-2012



(a) State

(b) County

Notes. This figure presents the change in the rate of OxyContin misuse between 2008 and 2012 across quartiles of the exposure measure at the state and county levels. Figure (a) plots the change in OxyContin misuse rates against quartiles of states' pre-reformulation OxyContin misuse rates. Figure (b) plots the change in OxyContin misuse rates against quartiles of counties' pre-reformulation Schedule II opioid prescriptions per capita. In both figures, OxyContin misuse rates are based on the measure from Alpert, Powell and Pacula (2018).

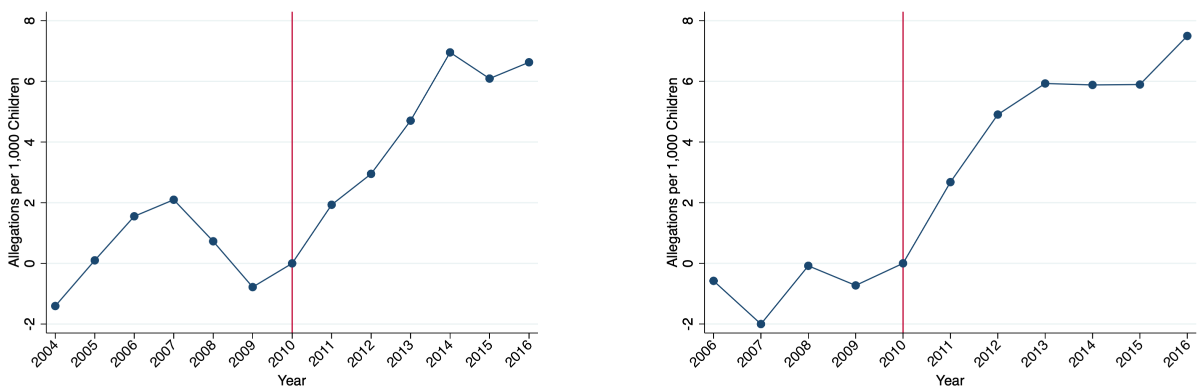
and counties with higher exposure measures experienced larger declines in the OxyContin misuse rates following the reformulation. Regression results with covariates are reported in Table A1. These results are consistent with the findings of Alpert, Powell and Pacula (2018) and Evans, Harris and Kessler (2022), which show that the reformulation of OxyContin had a greater impact in states with higher levels of nonmedical OxyContin use and in counties with higher rates of Schedule II prescription opioid dispensing prior to the reformulation.

The second assumption requires that the pre-reformulation OxyContin misuse rates and Schedule II prescription opioids per capita 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

Figure 3: Differential Trends in Maltreatment Allegations per 1,000 Children



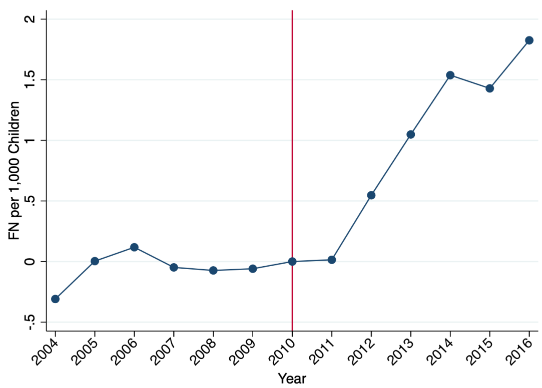
(a) Allegations by State

(b) Allegations by County

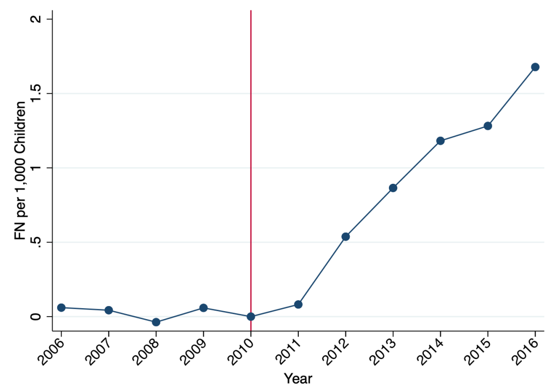
Notes. This figure illustrates the trends in the differences in maltreatment allegations per 1,000 children between high- and low-exposure states and counties. High-exposure states refer to states where the pre-reformulation (2004-2009) OxyContin misuse rates are above the median. High-exposure counties refer to counties where the pre-reformulation (2006-2009) Schedule II opioid prescriptions per capita are above the median.

Before presenting the main event study and difference-in-differences results, I examine differential trends in outcomes between high- and low-exposure states and counties. High-exposure states are defined as those where pre-reformulation (2004–2009) OxyContin misuse rates are above the median, while high-exposure counties are those where pre-reformulation (2006–2009) Schedule II opioid prescriptions per capita are above the median. Figure 3 presents trends in maltreatment allegations per 1,000 children. Prioir to the reformulation in 2010, the differences in maltreatment allegations are bounded between -2 and 2 at the state level and between -2 and 0 at the county level. These differences increased substantially following the reformulation, suggesting that regions more heavily affected by the opioid supply disruption experienced relatively larger increases in maltreatment allegations.

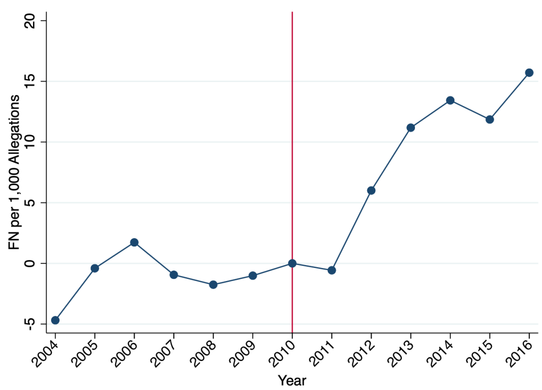
Figure 4: Differential Trends in False Negative Rates



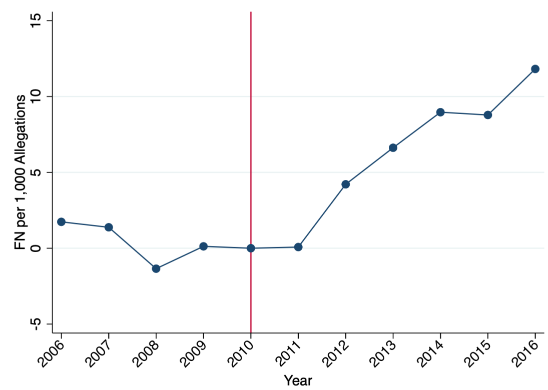
(a) FN by State, per 1,000 Children



(b) FN by County, per 1,000 Children



(c) FN by State, per 1,000 Allegations



(d) FN by County, per 1,000 Allegations

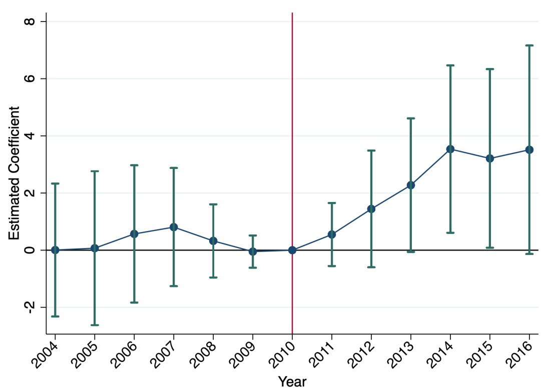
Notes. This figure illustrates the trends in the differences in false negatives per 1,000 children and 1,000 allegations between high- and low-exposure states and counties. High-exposure states refer to states where the pre-reformulation (2004-2009) OxyContin misuse rates are above the median. High-exposure counties refer to counties where the pre-reformulation (2006-2009) Schedule II opioid prescriptions per capita are above the median.

Figure 4 presents differential trends in false negatives per 1,000 children and 1,000 allegations. Prior to the reformulation, the differences in false negatives were close to zero across both measures. Following the reformulation, these differences increased substantially, suggesting that relatively more at-risk children were left in their homes in high-exposure states and counties.

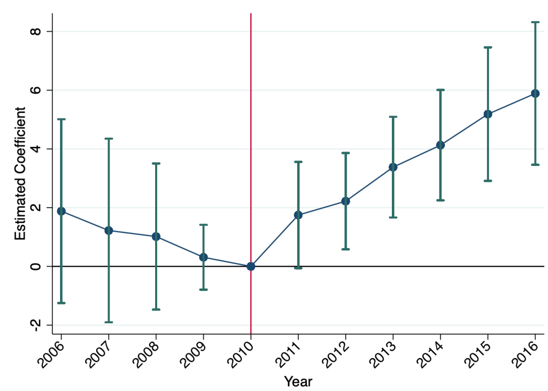
6.B Main Results

6.B.1 Maltreatment Allegations

Figure 5: Event Study Results for Allegations per 1,000 Children



(a) Allegations by State



(b) Allegations by County

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 and Equation 2 that are adjusted for within-state clustering. The dependent variable is maltreatment allegations reported by professionals per 1,000 children. Regressions are weighted by child population.

Figure 5 and Table 2 present the event study and difference-in-differences results for allegations per 1,000 children. Allegations increased at both the state and county levels. At the state level, a one standard deviation increase in the pre-reformulation OxyContin misuse rate corresponds to a 6% increase in the allegations in the short run, followed by a 14% increase in the medium run. At the county level, a one standard deviation increase in pre-reformulation Schedule II prescription opioids per capita yields a 10% and 21% increase in the allegations in the short and medium run, respectively.

An increase in the allegations indicates that the underlying maltreatment risk increased

Table 2: Difference-in-Differences Results for Allegations per 1,000 Children

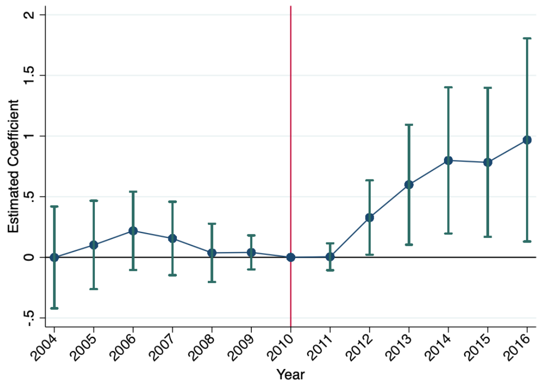
	(1) Allegations State	(2) Allegations County
Pre-reformulation	0.299	1.096
	(0.816)	(1.172)
Short-run	1.394*	2.433***
	(0.825)	(0.818)
	[5.7%]	[10.1%]
Medium-run	3.327**	5.021***
	(1.548)	(1.032)
	[13.7%]	[20.9%]
Mean (2010)	23.976	23.976
Adjusted R^2	0.871	0.858
Observations	634	7073
α_s or α_c	Yes	Yes
γ_t	Yes	Yes
X_{st} or X_{ct}	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are maltreatment allegations reported by professionals per 1,000 children. Columns (1) is based on a state-level analysis whereas Columns (2) is based on a county-level analysis. 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

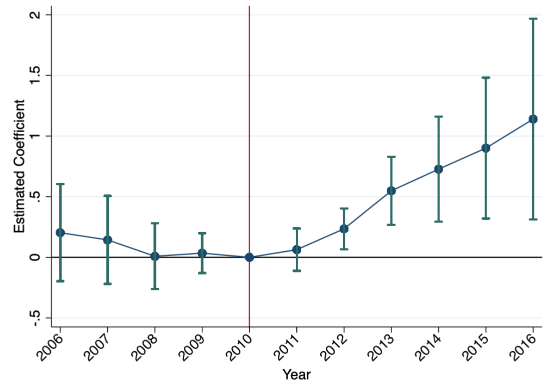
following the reformulation of OxyContin. The magnitudes of the effects are larger in the medium-run, which are consistent with the existing literature documenting the rise in the opioid overdose deaths, use of heroin and synthetic opioids, cases of Hepatitis and HIV, homicides and heroin-related arrests. In addition, these results suggest that the epidemic may have strained the child welfare system by increasing the volume of investigations faced by CPS.

6.B.2 False Negative Rate

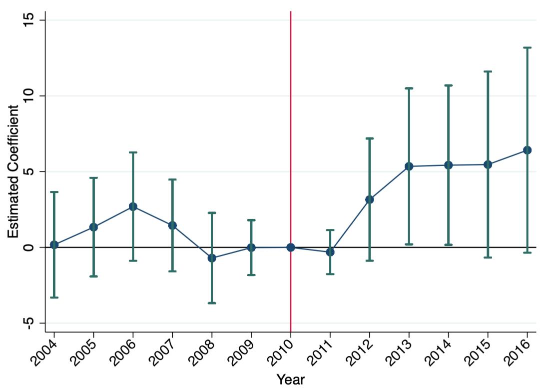
Figure 6: Event Study Results for False Negative Rates



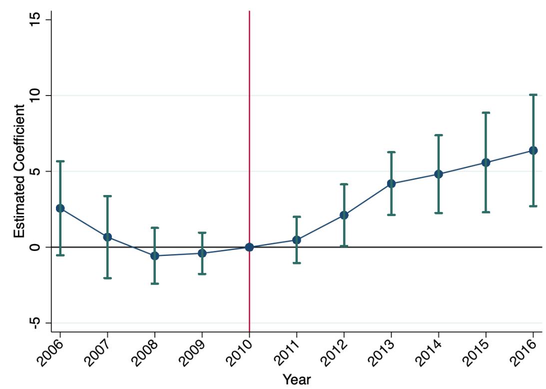
(a) FN by State, per 1,000 Children



(b) FN by County, per 1,000 Children



(c) FN by State, per 1,000 Allegations



(d) FN by County, 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 and Equation 2 that are adjusted for within-state clustering. The dependent variables are foster care placements and false negatives per 1,000 allegations. Regressions are weighted by child population.

Figure 6 and Table 3 present the results for false negative rates. These results suggest that the false negative rates significantly increased following the reformulation. A one standard deviation increase in the pre-reformulation OxyContin misuse rate yields a 12.8% and 34.4% increase in the false negatives per 1,000 children in the short and medium run, respectively.

Table 3: Difference-in-Differences Results for False Negative Rates

	(1) FN Children State	(2) FN Children County	(3) FN Allegations State	(4) FN Allegations County
Pre-reformulation	0.087	0.098	0.699	0.515
	(0.119)	(0.134)	(1.202)	(1.344)
Short-run	0.301**	0.275***	2.651	2.223**
	(0.129)	(0.066)	(1.600)	(0.839)
	[12.8%]	[11.7%]	[4.7%]	[3.9%]
Medium-run	0.809**	0.899***	5.415*	5.490**
	(0.321)	(0.295)	(2.831)	(2.308)
	[34.4%]	[38.3%]	[9.6%]	[9.7%]
Mean (2010)	2.35	2.35	56.373	56.373
Adjusted R^2	0.874	0.871	0.872	0.858
Observations	637	634	7073	7073
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are false negatives rates. Columns (1) and (2) report the results for false negatives per 1,000 children whereas Columns (3) and (4) report the results for false negatives per 1,000 allegations. Columns (1) and (3) are based on a state-level analysis whereas Columns (2) and (4) are based on a county-level analysis. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

At the county level, a one standard deviation increase in the pre-reformulation Schedule II prescription opioids per capita yields a 11.7% and 38.3% increase in the short and medium run, respectively.

These findings suggest that more children in the population were exposed to maltreatment risk following the reformulation, as reflected by the rise in maltreatment allegations, and that an increasing number of at-risk children were left at home. More broadly, they indicate that the opioid epidemic systematically increased the number of children harmed without adequate institutional intervention, highlighting its broad consequences for child welfare. While this is a striking result, it is important to acknowledge that some of the increase in false negatives may occur mechanically due to an increase in the allegations. By definition, a false negative requires that a child is at risk, reported to CPS, and subsequently left at home. As such, conditional on a fixed decision rule, an increase in the number of allegations can lead to more false negatives simply due to a larger pool of reported children. Therefore, while the rise in false negatives per 1,000 children is a meaningful indicator of the opioid epidemic's broader impact on child welfare at the population level, it may not fully reflect CPS responses to the opioid epidemic.

However, an increase in the false negatives per 1,000 allegations suggests that such patterns are not solely driven by a larger pool of reported children. At the state level, a one standard deviation increase in the pre-reformulation OxyContin misuse rate yields a 10% increase in the false negatives per 1,000 allegations in the medium run. At the county level, a one standard deviation increase in pre-reformulation opioid prescriptions per capita yields a 4% and 10% increase in the short and medium run, respectively. These results indicate that CPS systemically left more at-risk children at home conditional on allegations following the reformulation.

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

Figures A5 and A6, along with Tables A5 and A6, 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 higher rate than for Black children. 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.

Figures A1, A2, A3, and A4, along with Tables A3 and A4, 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.

Figures A7, A9, A8, A10, A12 and A11, along with Tables A8, A7, A10, and A9 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. The rise was more pronounced for White children than for Black children, measured per 1,000 children, suggesting that a greater number of at-risk White children were left at home unprotected following the reformulation. This pattern is largely driven by the disproportionate impact of the opioid epidemic on White children, increasing the the number of at-risk White children slipping through the system.

6.D Robustness Checks

Figures A14, A13 and Tables A12, A11 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 risk and CPS placement decisions. Figures A16, A15 and Tables A14, A13 present the results based on the alternative time frames for defining false negatives. The results are robust to subsequent allegations within 3 months, 9 months, and 12 months following the initial investigation.

Figure A17 and Table A15 present the event study and difference-in-differences results for false negatives based on the provision of services. Children and families involved in child welfare investigations may receive post-reponse services between the report date and up to 90 days after the disposition date. Post-response 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.[9] An alternative measure of false negatives would be to define it as a case where the reported child was not provided with post-response service but was reported within 6 months of the focal investigation. Figure A17 and Table A15 show that the false negative rate based on this measure increased following the reformulation,

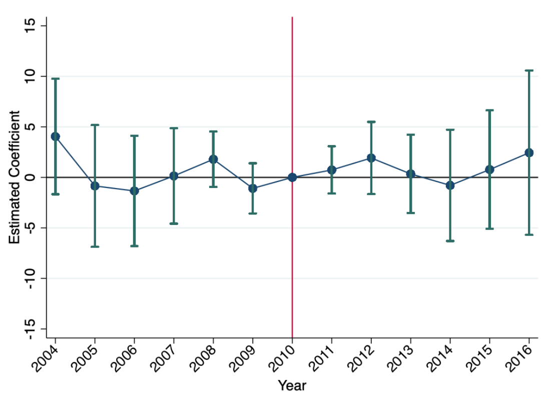
[9]Post-response services include the following: family support, family preservation, foster care, adoption, case management, counseling, day care, education and training, employment, family planning, health-related and home health, home-based, housing, independent and transitional living, information and referral, legal, mental health, pregnancy and parenting, respite care, special, substance abuse, and transportation services.

consistent with results based on the definition of false negatives using foster care placements as a treatment.

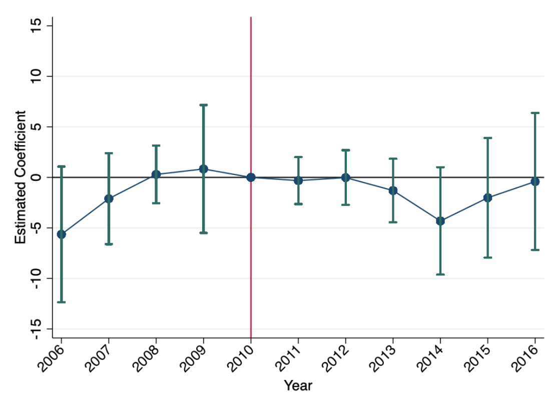
Alternative empirical specifications have been estimated for robustness checks. Figures A18 and A19, along with Tables A16 and A17, present results based on a binary treatment, where the exposure measure is defined as an indicator taking the value of one if the state's pre-reformulation OxyContin misuse rate is above the median and if the county's pre-reformulation opioid prescriptions per capita are above the median. Finally, Figures A20 and A21, along with Tables A18 and A19, 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 7: Event Study Results for Placement per 1,000 Allegations



(a) Placement Rates by State



(b) Placement Rates by County

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 and Equation 2 that are adjusted for within-state clustering. The dependent variables are foster care placements per 1,000 allegations. Figure (a) is based on state-level analyses, whereas Figure (b) is based on county-level analyses. Regressions are weighted by child population.

Table 4: Difference-in-Differences Results for Placement Rates

	(1) State Placement	(2) County Placement
Pre-reformulation	0.318	-1.451
	(1.649)	(1.738)
Short-run	0.987	-0.617
	(1.492)	(1.128)
	[1.8%]	[-1.1%]
Medium-run	0.797	-2.487
	(2.965)	(2.866)
	[1.4%]	[-4.4%]
Mean (2010)	56.158	56.158
Adjusted R^2	0.760	0.743
Observations	559	5544
α_s or α_c	Yes	Yes
γ_t	Yes	Yes
X_{st} or X_{ct}	Yes	Yes

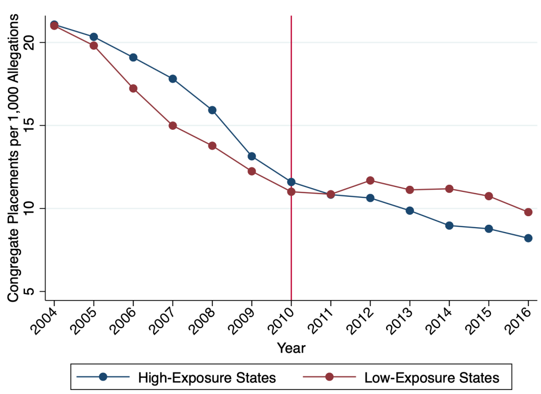
Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are foster care placements per 1,000 allegations. Column (1) is based on a state-level analysis whereas Columns (2) and (4) is based on a county-level analysis. Regressions are 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This section explores potential mechanisms for a rise in the false negatives conditional on allegations. I explore two channels: (1) changes in the foster care placements conditional on allegations and (2) capacity constraints. As demonstrated in section 4, a key driver of the rise in false negative rates is the stagnant changes in the placement rate for at-risk children despite an increase in underlying risk. In addition, the supply of foster homes may affect placement decisions.

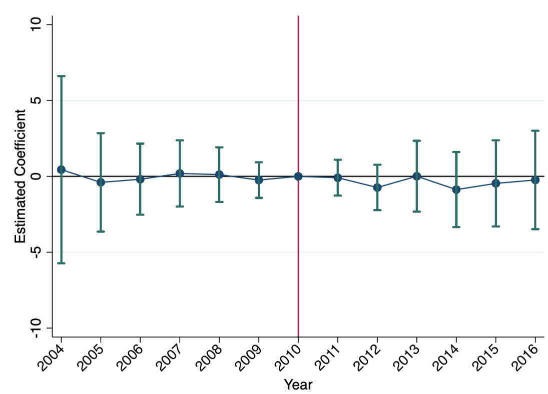
Figure 7 and Table 4 present the event study and difference-in-differences results for foster care placement rates. The results show that changes in foster care placements per 1,000 allegations were statistically indistinguishable from zero. Tables A20 and A21 show that these results hold across maltreatment types and demographics of the children. These results suggest that CPS did not adjust placement thresholds in response to the rising severity of allegations, resulting in more at-risk children being left at home. These findings provide suggestive evidence of rule-of-thumb placement norms, in which placement decisions follow a predetermined cap or target rate in each period rather than responding dynamically to changes in underlying risk.

A stagnant change in the foster care placement rate in response to a rise in the risk may be attributed to a shortage of available 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, a structured, supervised setting where multiple children or youth live together rather than in a family-based environment. Congregate care includes group homes, which are licensed or approved facilities providing 24-hour care for generally 7 to 12 children, and institutions, larger facilities operated by public or private agencies that care for more than 12 children.

Figure 8: Congregate Placement Rate



(a) Trends



(b) Event Study

Notes. Figure (a) illustrates the trends in congregate placements per 1,000 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. 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, where the dependent variable is congregate placements per 1,000 allegations.

Table 5: Difference-in-Differences Results for Congregate Placement Rate

	(1)
Pre-reformulation	-0.036
	(1.079)
Short-run	-0.275
	(0.772)
	[-2.5%]
Medium-run	-0.548
	(1.362)
	[-4.9%]
Mean (2010)	11.221
Adjusted R^2	0.875
Observations	506
α_s	Yes
γ_t	Yes
X_{st}	Yes

Notes. This table reports point estimates and standard errors from Equation 3, where the dependent variable is congregate placements per 1,000 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Congregate care is generally considered a last resort for foster children (Bald et al., 2022*b*). Research has documented negative outcomes for children in congregate care and congregate placement rates have gradually declined (Lee and Thompson, 2008; Ryan et al., 2008; Robst, Armstrong and Dollard, 2011). Figure 8 shows these trends, with congregate placements per 1,000 allegations declining in both high- and low-exposure states. If foster home shortages were more severe in high-exposure states, congregate placement rates would likely have increased more or declined less in those states relative to low-exposure states.

For the analysis of capacity constraints, I use the same subsample of 38 states and Washington, D.C., as in the false negative analysis. This analysis is conducted at the state level only, as the AFCARS Foster Care Files mask data for counties with fewer than 700 foster care placements, resulting in most counties being excluded. Figure 8 and Table 5 presents the event study and difference-in-differences results for congregate placements rates. The results suggest that the congregate placement rate remained stable following the reformulation. This suggests that a foster home shortage has not been the primary driver of trends in foster care placements.

8 Conclusion

The consequences of public health crises often extend beyond the health care system and place substantial strain on other critical public institutions. The opioid epidemic, widely regarded as the worst drug overdose crisis in U.S. history, has had far-reaching impacts and imposed substantial costs on society. Given the strong association between parental substance abuse and child maltreatment, understanding the effects of the opioid epidemic on child welfare and evaluating the responsiveness of CPS to mitigate these consequences are critical areas of academic and public policy research.

Leveraging cross-state variation in pre-reformulation OxyContin misuse rates and cross-county variation in pre-reformulation prescription opioids per capita, I present three key findings. First, maltreatment allegations increased significantly after the reformulation, consistent with previous studies documenting the unintended consequences of supply-side drug policies during the opioid epidemic. Second, more at-risk children were left at home, as evidenced by the increase in the false negative rate. Lastly, I find that changes in foster care placements following the reformulation were insignificant, and that a shortage of foster homes was not a primary driver of this response.

The findings of this paper uncover the impacts of the opioid epidemic on child welfare as well as its spillover effects on public institutions beyond the health care system. Given the long-term consequences of child maltreatment, including lower educational attainment, poorer health, and diminished economic mobility, the results suggest that the opioid epidemic may have long-lasting intergenerational impacts. More broadly, the findings underscore how public health shocks can strain protective institutions tasked with safeguarding vulnerable populations.

In addition, this paper emphasizes the critical importance of responsive foster care placement policies during periods of heightened maltreatment risk. Policymakers should consider developing mechanisms that allow CPS to adjust placement thresholds dynamically in response to credible signals of heightened maltreatment risk. When such shocks occur, they often lead to a surge in maltreatment allegations, placing significant strain on the system through rising caseloads and limited resources. Policymakers must be prepared to respond by scaling staff capacity and resources accordingly. Additional measures may include investing in data infrastructure to improve risk assessment accuracy, introducing greater flexibility in placement decision guidelines, and establishing early warning systems to trigger targeted resource deployment during crises. More broadly, aligning protective services with real-time changes in risk exposure is essential to minimizing the long-term developmental and economic costs of unaddressed child maltreatment.

References

Alpert, Abby, David Powell, and Rosalie Liccardo Pacula. 2018. "Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids." *American Economic Journal: Economic Policy*, 10(4): 1–35.

Alpert, Abby, William N Evans, Ethan MJ Lieber, and David Powell. 2022. "Origins of the opioid crisis and its enduring impacts." *The Quarterly Journal of Economics*, 137(2): 1139–1179.

Antle, Becky F, Anita P Barbee, Dana N Christensen, and Dana J Sullivan. 2009. "The prevention of child maltreatment recidivism through the solution-based casework model of child welfare practice." *Children and Youth Services Review*, 31(12): 1346–1351.

Arteaga, Carolina, and Victoria Barone. 2022. "A manufactured tragedy: The origins and deep ripples of the opioid epidemic." Working paper. http://www. carolina. com/s/Opioids_ArteagaBarone_Jan2022. pdf.

Bald, Anthony, Eric Chyn, Justine Hastings, and Margarita Machelett. 2022*a*. "The causal impact of removing children from abusive and neglectful homes." *Journal of Political Economy*, 130(7): 1919–1962.

Bald, Anthony, Joseph J Doyle Jr, Max Gross, and Brian A Jacob. 2022*b*. "Economics of foster care." *Journal of Economic Perspectives*, 36(2): 223–246.

Baron, E Jason, and Max Gross. 2022. "Is there a foster care-to-prison pipeline? Evidence from quasi-randomly assigned investigators." *National Bureau of Economic Research.*

Baron, E Jason, Joseph J Doyle Jr, Natalia Emanuel, Peter Hull, and Joseph Ryan. 2024*a*. "Discrimination in Multiphase Systems: Evidence from Child Protection." *The Quarterly Journal of Economics*, qjae007.

Baron, E Jason, Richard Lombardo, Joseph P Ryan, Jeongsoo Suh, and Quitze Valenzuela-Stookey. 2024*b*. "Mechanism Reform: An Application to Child Welfare." *National Bureau of Economic Research.*

Beheshti, David. 2019. "Adverse health effects of abuse-deterrent opioids: Evidence from the reformulation of OxyContin." *Health economics*, 28(12): 1449–1461.

Borgschulte, Mark, Adriana Corredor-Waldron, and Guillermo Marshall. 2018. "A path out: Prescription drug abuse, treatment, and suicide." *Journal of Economic Behavior & Organization*, 149: 169–184.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-experimental shift-share research designs." *The Review of economic studies*, 89(1): 181–213.

Brooks-Gunn, Jeanne, William Schneider, and Jane Waldfogel. 2013. "The Great Recession and the risk for child maltreatment." *Child abuse & neglect*, 37(10): 721–729.

Buchmueller, Thomas C, and Colleen Carey. 2018. "The effect of prescription drug monitoring programs on opioid utilization in Medicare." *American Economic Journal: Economic Policy*, 10(1): 77–112.

Burgess, Diana J, Michelle Van Ryn, Megan Crowley-Matoka, and Jennifer Malat. 2006. "Understanding the provider contribution to race/ethnicity disparities in pain treatment: insights from dual process models of stereotyping." *Pain Medicine*, 7(2): 119–134.

Bush, Donna M, and Rachel N Lipari. 2016. "Substance use and substance use disorder by industry." Substance Abuse and Mental Health Services Administration.

CDC. 2023. "Understanding the Opioid Overdose Epidemic." *https://www.cdc.gov/opioids/basics/epidemic.html*.

Chang, Roberto, Linda Kaltani, and Norman V Loayza. 2009. "Openness can be good for growth: The role of policy complementarities." *Journal of development economics*, 90(1): 33–49.

Children's Bureau. 2022. "Child Maltreatment 2015-2022." *https://www.acf.hhs.gov/cb/report/child-maltreatment-2022*.

Cicero, Theodore J, and Matthew S Ellis. 2015. "Abuse-deterrent formulations and the prescription opioid abuse epidemic in the United States: lessons learned from OxyContin." *JAMA psychiatry*, 72(5): 424–430.

Cicero, Theodore J, James A Inciardi, and Alvaro Muñoz. 2005. "Trends in abuse of OxyContin® and other opioid analgesics in the United States: 2002-2004." *The Journal of Pain*, 6(10): 662–672.

Coe, David T, and Dennis J Snower. 1997. "Policy complementarities: the case for fundamental labor market reform." *Staff Papers*, 44(1): 1–35.

Conners-Burrow, Nicola A, Betsy Johnson, and Leanne Whiteside-Mansell. 2009. "Maternal substance abuse and children's exposure to violence." *Journal of Pediatric Nursing*, 24(5): 360–368.

Coplan, Paul M, Hrishikesh Kale, Lauren Sandstrom, Craig Landau, and Howard D Chilcoat. 2013. "Changes in oxycodone and heroin exposures in the National Poison Data System after introduction of extended-release oxycodone with abuse-deterrent characteristics." *Pharmacoepidemiology and drug safety*, 22(12): 1274–1282.

Dobkin, Carlos, and Nancy Nicosia. 2009. "The war on drugs: methamphetamine, public health, and crime." *American Economic Review*, 99(1): 324–349.

Dobkin, Carlos, Nancy Nicosia, and Matthew Weinberg. 2014. "Are supply-side drug control efforts effective? Evaluating OTC regulations targeting methamphetamine precursors." *Journal of Public Economics*, 120: 48–61.

Doyle Jr, Joseph J. 2007. "Child protection and child outcomes: Measuring the effects of foster care." *American Economic Review*, 97(5): 1583–1610.

Doyle Jr, Joseph J. 2008. "Child protection and adult crime: Using investigator assignment to estimate causal effects of foster care." *Journal of political Economy*, 116(4): 746–770.

Evans, Mary F, Ludovica Gazze, and Jessamyn Schaller. 2023. "Temperature and maltreatment of young children." *National Bureau of Economic Research*.

Evans, Mary F, Matthew C Harris, and Lawrence M Kessler. 2022. "The hazards of unwinding the prescription opioid epidemic: Implications for child maltreatment." *American Economic Journal: Economic Policy*, 14(4): 192–231.

Evans, William N, Ethan MJ Lieber, and Patrick Power. 2019. "How the reformulation of OxyContin ignited the heroin epidemic." *Review of Economics and Statistics*, 101(1): 1–15.

Font, Sarah A, and Ezra G Goldstein. 2024. "Maternal Substance Use Disorder and Child Welfare Involvement: Prevalence and Treatment." *Working Paper*.

Gihleb, Rania, Osea Giuntella, and Ning Zhang. 2022. "The Effect of Mandatory-Access Prescription Drug Monitoring Programs on Foster Care Admissions." *Journal of Human Resources*, 57(1): 217–240.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik instruments: What, when, why, and how." *American Economic Review*, 110(8): 2586–2624.

Grecu, Anca M, Dhaval M Dave, and Henry Saffer. 2019. "Mandatory access prescription drug monitoring programs and prescription drug abuse." *Journal of Policy Analysis and Management*, 38(1): 181–209.

Gross, Max, and E Jason Baron. 2022. "Temporary stays and persistent gains: The causal effects of foster care." *American Economic Journal: Applied Economics*, 14(2): 170–199.

Harris, Matthew C, Lawrence M Kessler, Matthew N Murray, and Beth Glenn. 2020. "Prescription opioids and labor market pains: the effect of schedule II opioids on labor force participation and unemployment." *Journal of Human Resources*, 55(4): 1319–1364.

Hartzema, Abraham G, Miquel S Porta, Hugh H Tilson, Sergio G Zullich, Thaddeus H Grasela Jr, Jill B Fiedler-Kelly, and Francis M Gengo. 1992. "Impact of triplicate prescription program on psychotropic prescribing patterns in long-term care facilities." *Annals of Pharmacotherapy*, 26(4): 539–546.

Hawkins, Devan, Cora Roelofs, James Laing, and Letitia Davis. 2019. "Opioid-related overdose deaths by industry and occupation—Massachusetts, 2011-2015." *American journal of industrial medicine*, 62(10): 815–825.

Health-Americas, The Lancet Regional. 2023. "Opioid crisis: addiction, overprescription, and insufficient primary prevention." *Lancet Regional Health-Americas*, 23.

Jones, Mark R, Omar Viswanath, Jacquelin Peck, Alan D Kaye, Jatinder S Gill, and Thomas T Simopoulos. 2018. "A brief history of the opioid epidemic and strategies for pain medicine." *Pain and therapy*, 7: 13–21.

Kolodny, Andrew, David T Courtwright, Catherine S Hwang, Peter Kreiner, John L Eadie, Thomas W Clark, and G Caleb Alexander. 2015. "The prescription opioid and heroin crisis: a public health approach to an epidemic of addiction." *Annual review of public health*, 36: 559–574.

Larochelle, Marc R, Fang Zhang, Dennis Ross-Degnan, and J Frank Wharam. 2015. "Rates of opioid dispensing and overdose after introduction of abuse-deterrent extended-release oxycodone and withdrawal of propoxyphene." *JAMA internal medicine*, 175(6): 978–987.

Lee, Bethany R, and Ron Thompson. 2008. "Comparing outcomes for youth in treatment foster care and family-style group care." *Children and Youth Services Review*, 30(7): 746–757.

Leslie, Douglas L, Djibril M Ba, Edeanya Agbese, Xueyi Xing, and Guodong Liu. 2019. "The economic burden of the opioid epidemic on states: the case of Medicaid." *Am J Manag Care*, 25(13 Suppl): S243–S249.

Mallatt, Justine. 2022. "Policy-induced substitution to illicit drugs and implications for law enforcement activity." *American Journal of Health Economics*, 8(1): 30–64.

MDHHS. 2020. "Children's Protective Services Policy Manuals." *https://mplp.org/sites/default/files/2020-08/child-protective-services-manual.pdf*.

Meinhofer, Angelica. 2016. *The war on drugs: Estimating the effect of prescription drug supply-side interventions.* Vol. 2716974, SSRN.

Monico, Laura B, and Shannon Gwin Mitchell. 2018. "Patient perspectives of transitioning from prescription opioids to heroin and the role of route of administration." *Substance Abuse Treatment, Prevention, and Policy*, 13: 1–8.

NCDHHS. 2024. "NC CHILD WELFARE MANUAL." *https://policies.ncdhhs.gov/wp-content/uploads/CPS-Assessments-Aug-2024.pdf*.

NCHS. 2023. "Data retrieved from the National Vital Statistics System." *https://www.cdc.gov/nchs/index.htm*.

Netherland, Julie, and Helena B Hansen. 2016. "The war on drugs that wasn't: Wasted whiteness,"dirty doctors," and race in media coverage of prescription opioid misuse." *Culture, Medicine, and Psychiatry*, 40: 664–686.

Nicolette Harris, DAT, Samar Long, et al. 2021. "Racial and Ethnic Disparities in Pain Management." *Clinical Practice in Athletic Training*, 4(1).

Orszag, J Michael. 1998. "Anatomy of policy complementarities." CEPR Discussion Paper Series.

Park, Sujeong. 2022. "The Growth of Illicit Drug Use and Its Effects on Murder Rates." *Health Economics*.

Phillips, Donald M. 2000. "JCAHO pain management standards are unveiled." *Jama*, 284(4): 428–429.

Powell, David, and Rosalie Liccardo Pacula. 2021. "The evolving consequences of oxycontin reformulation on drug overdoses." *American Journal of Health Economics*, 7(1): 41–67.

Powis, Michael Gossop, Catherine Bury, Katherine Payne, Paul Griffiths, and Beverly. 2000. "Drug-using mothers: social, psychological and substance use problems of women opiate users with children." *Drug and Alcohol Review*, 19(2): 171–180.

Putnam-Hornstein, Emily, John Prindle, and Ivy Hammond. 2021. "Engaging families in voluntary prevention services to reduce future child abuse and neglect: A randomized controlled trial." *Prevention science*, 22(7): 856–865.

Putnam-Hornstein, Emily, Julie A Cederbaum, Bryn King, Andrea L Eastman, and Penelope K Trickett. 2015. "A population-level and longitudinal study of adolescent mothers and intergenerational maltreatment." *American journal of epidemiology*, 181(7): 496–503.

Raitasalo, Kirsimarja, and Marja Holmila. 2017. "Parental substance abuse and risks to children's safety, health and psychological development." *Drugs: Education, Prevention and Policy*, 24(1): 17–22.

Robst, John, Mary Armstrong, and Norin Dollard. 2011. "Comparing outcomes for youth served in treatment foster care and treatment group care." *Journal of Child and Family Studies*, 20: 696–705.

Rutherford, Helena JV, and Linda C Mayes. 2017. "Parenting and addiction: Neurobiological insights." *Current opinion in psychology*, 15: 55–60.

Ryan, Joseph P, Jane Marie Marshall, Denise Herz, and Pedro M Hernandez. 2008. "Juvenile delinquency in child welfare: Investigating group home effects." *Children and Youth Services Review*, 30(9): 1088–1099.

Sabin, Janice A, Brian A Nosek, Anthony G Greenwald, and Frederick P Rivara. 2009. "Physicians' implicit and explicit attitudes about race by MD race, ethnicity, and gender." *Journal of health care for the poor and underserved*, 20(3): 896–913.

Santoro, Taylor N, and Jonathan D Santoro. 2018. "Racial bias in the US opioid epidemic: a review of the history of systemic bias and implications for care." *Cureus*, 10(12).

Sigler, Katherine A, Brock G Guernsey, Naomi B Ingrim, Amy S Buesing, James A Hokanson, Eustacio Galvan, and William H Doutré. 1984. "Effect of a triplicate prescription law on prescribing of Schedule II drugs." *American Journal of Hospital Pharmacy*, 41(1): 108–111.

Simoni-Wastila, Linda, Dennis Ross-Degnan, Connie Mah, Xiaoming Gao, Jeffrey Brown, Leon E Cosler, Thomas Fanning, Peter Gallagher, Carl Salzman, and Stephen B Soumerai. 2004. "A retrospective data analysis of the impact of the New York triplicate prescription program on benzodiazepine use in medicaid patients with chronic psychiatric and neurologic disorders." *Clinical therapeutics*, 26(2): 322–336.

Sim, Yongbo. 2023. "The effect of opioids on crime: Evidence from the introduction of OxyContin." *International Review of Law and Economics*, 74: 106136.

Soliman, Adam. 2023. *Disrupting Drug Markets: The Effects of Crackdowns on Rogue Opioid Suppliers.* SSRN.

Tan, Bowen. 2024. "The Effects of OxyContin Reformulation on Homicides." *Working Paper.*

Walsh, Christine, Harriet L MacMillan, and Ellen Jamieson. 2003. "The relationship between parental substance abuse and child maltreatment: findings from the Ontario Health Supplement." *Child abuse & neglect*, 27(12): 1409–1425.

Weintraub, Michael, Satesh Singh, Louise Byrne, Kumar Maharaj, and Laurence Guttmacher. 1991. "Consequences of the 1989 New York State triplicate benzodiazepine prescription regulations." *Jama*, 266(17): 2392–2397.

Wells, Kathryn. 2009. "Substance abuse and child maltreatment." *Pediatric Clinics of North America*, 56(2): 345–362.

White, Alan G, Howard G Birnbaum, Milena N Mareva, Maham Daher, Susan Vallow, Jeff Schein, and Nathaniel Katz. 2005. "Direct costs of opioid abuse in an insured population in the United States." *Journal of Managed Care Pharmacy*, 11(6): 469–479.

White, Helene Raskin, and Cathy Spatz Widom. 2008. "Three potential mediators of the effects of child abuse and neglect on adulthood substance use among women." *Journal of studies on alcohol and drugs*, 69(3): 337–347.

Wildeman, Christopher, and Natalia Emanuel. 2014. "Cumulative risks of foster care placement by age 18 for US children, 2000–2011." *PloS one*, 9(3): e92785.

Appendix

Child Protection in Response to Public Health Crises: Evidence from the Opioid Epidemic

Jeongsoo Suh

A First Stage Regression

Table A1: First Stage Regressions

	(1) State	(2) State	(3) County	(4) County
Exposure	-0.184***	-0.121*	-0.110***	-0.068***
	(0.046)	(0.060)	(0.024)	(0.025)
Unemployment		0.048		0.048***
		(0.046)		(0.015)
Labor Force Participation		0.033*		0.015***
		(0.019)		(0.006)
Percent White		-0.002		-0.001
		(0.007)		(0.003)
Percent Black		0.022**		0.010***
		(0.009)		(0.003)
Percent Hispanic		0.009		0.005**
		(0.007)		(0.002)
Percent Female		-0.132		-0.054***
		(0.120)		(0.018)
Percent age 0 to 19		-0.022		0.001
		(0.052)		(0.027)
Percent age 20 to 24		-0.056		0.067**
		(0.146)		(0.026)
Percent age 25 to 34		0.032		-0.045
		(0.106)		(0.037)
Percent age 35 to 44		-0.080		0.045
		(0.139)		(0.050)
Percent age 45 to 54		0.300***		0.132**
		(0.105)		(0.063)
Percent age 55 to 64		-0.048		0.052
		(0.162)		(0.075)
Constant	-0.156***	1.702	-0.118***	-0.165
	(0.044)	(8.623)	(0.024)	(1.344)
Adjusted R^2	0.316	0.531	0.064	0.229
F Statistics	16.304	11.949	20.524	9.117
Observations	49	49	643	643

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 exposure measures. Columns (1) and (2) are based on a state-level analysis. Columns (3) and (4) are based on a county-level analysis. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Supplemental Summary Statistics

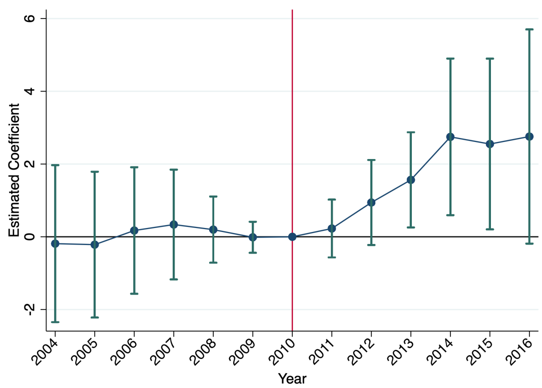
Table A2: Summary Statistics for Maltreatment Allegations

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
Relatives	7.3	-
Parent	6.5	-
Friends/Neighbors	5.2	-
Substitute Care Provider	0.4	-
Alleged Victim	0.4	-
Alleged Perpetrator	0.1	-
Anonymous Reporter	9.2	-
Unknown	14.6	-

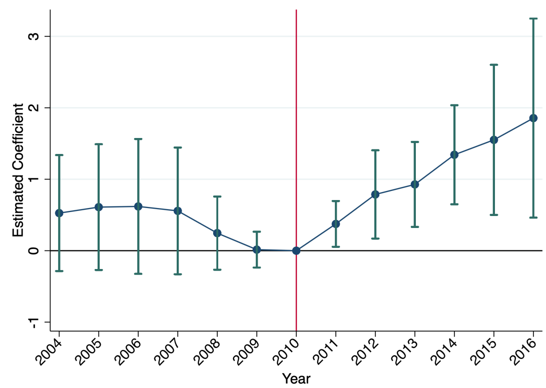
Notes. This table reports the percentage of allegations by maltreatment types, child characteristics, and report sources, separately for all allegations and for allegations made by professionals during the sample period from 2004 to 2016. Professional allegations refer to those reported by education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

C Allegations by Maltreatment Types and Report Sources - State

Figure A1: Allegations Reported by Professionals by Maltreatment Types - State



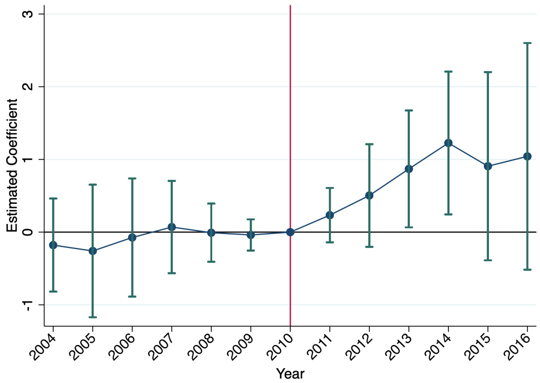
(a) Neglect



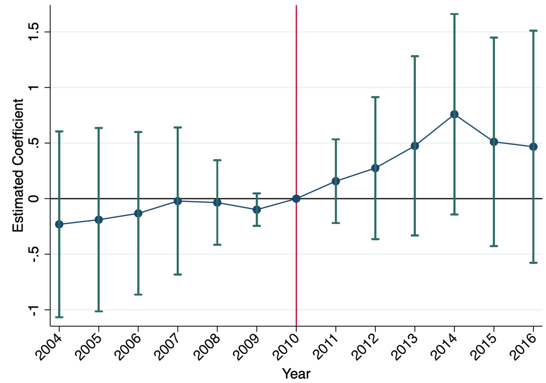
(b) Physical Abuse

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.

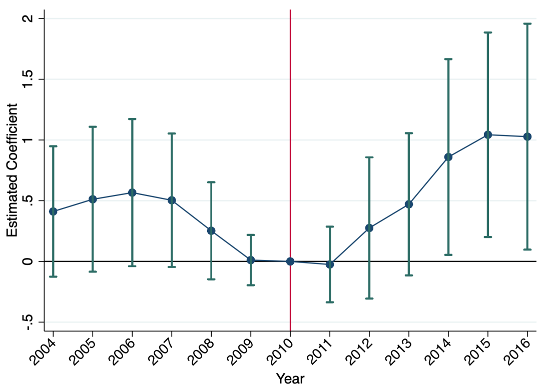
Figure A2: Maltreatment Allegations by Occupation - State



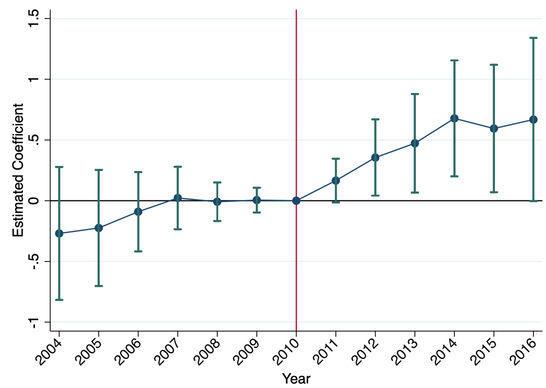
(a) Education Personnel



(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.

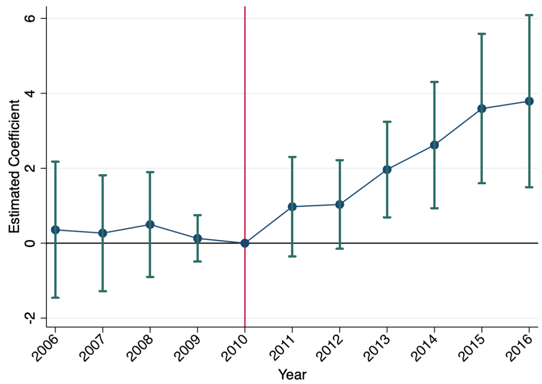
Table A3: Allegations by Maltreatment Type and Report Source - State

	(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
Adjusted R^2	0.826	0.673	0.824	0.919	0.842	0.838
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

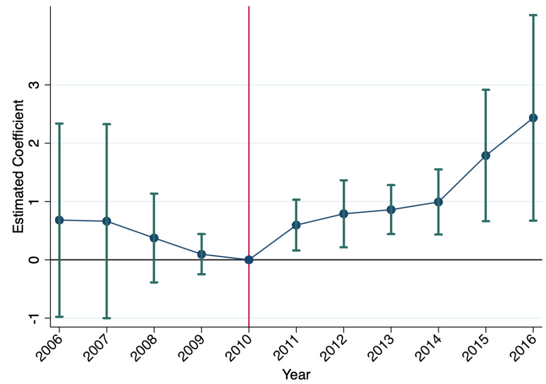
Notes. This table reports point estimates and standard errors from Equation 3, where dependent variables are maltreatment allegations reported by professionals per 1,000 children, broken down by report type and source. Regressions are weighted by child population. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D Allegations by Maltreatment Types and Report Sources - County

Figure A3: Allegations Reported by Professionals by Maltreatment Types - County



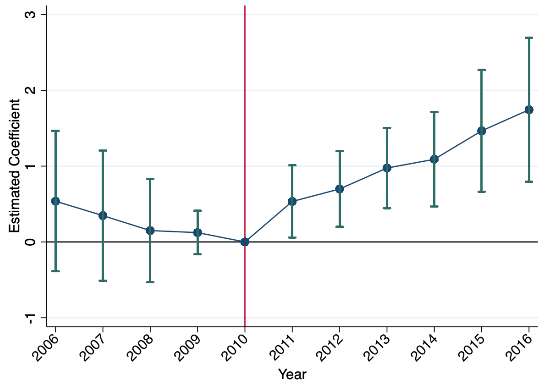
(a) Neglect



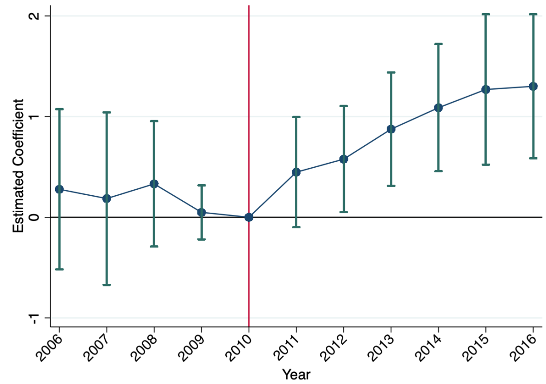
(b) Physical Abuse

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 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.

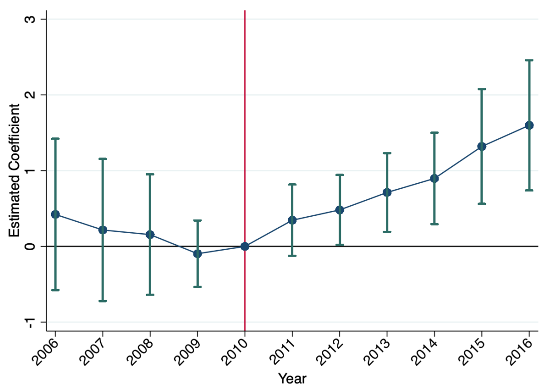
Figure A4: Maltreatment Allegations by Occupation - County



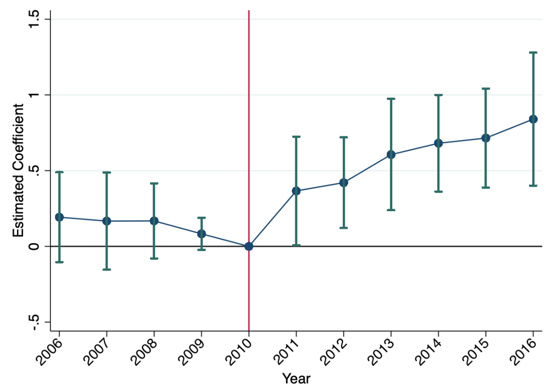
(a) Education Personnel



(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 2 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.

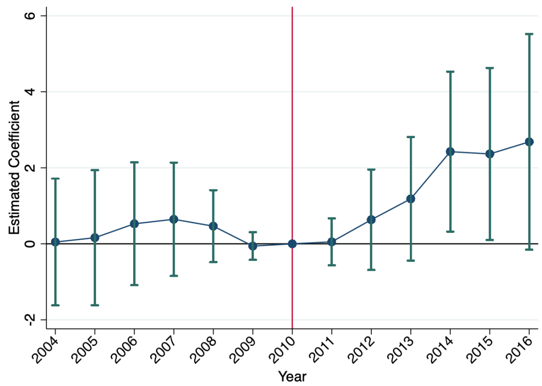
Table A4: Allegations by Maltreatment Type and Report Source - County

	(1) Neglect	(2) Physical	(3) Education	(4) Legal	(5) Social Services	(6) Medical
Pre-reformulation	0.329	0.450	0.287	0.213	0.170	0.154
	(0.606)	(0.531)	(0.318)	(0.301)	(0.375)	(0.110)
Short-run	1.309**	0.744***	0.731***	0.628**	0.509**	0.461***
	(0.599)	(0.222)	(0.222)	(0.263)	(0.230)	(0.167)
	[9.9%]	[12.8%]	[10.7%]	[8.8%]	[11.1%]	[14.5%]
Medium-run	3.281***	1.714***	1.418***	1.206***	1.258***	0.738***
	(0.894)	(0.552)	(0.363)	(0.346)	(0.351)	(0.155)
	[24.8%]	[28.1%]	[20.7%]	[16.9%]	[27.5%]	[23.5%]
Mean (2010)	13.237	6.105	6.839	7.122	4.58	3.146
Adjusted R^2	0.841	0.680	0.791	0.892	0.825	0.840
Observations	7073	7073	7073	7073	7073	7073
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

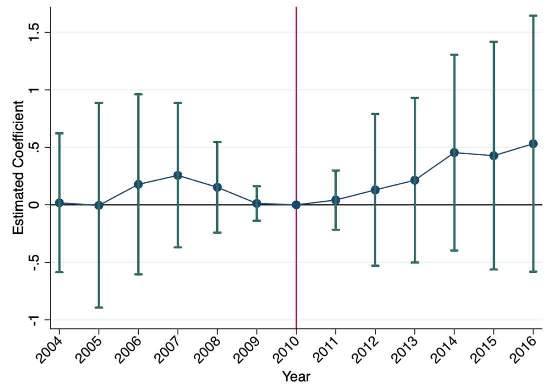
Notes. This table reports point estimates and standard errors from Equation 4, where dependent variables are maltreatment allegations reported by professionals per 1,000 children, broken down by report type and source. Regressions are weighted by child population. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

E Allegations by Child Characteristics - State

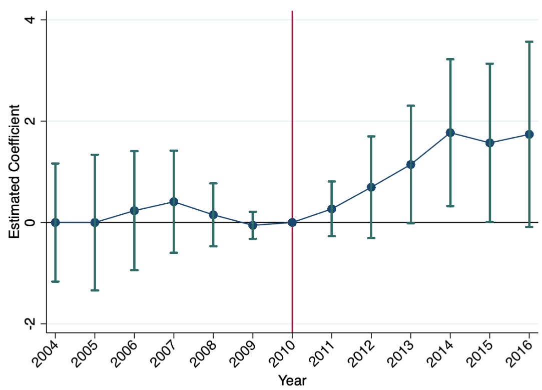
Figure A5: Maltreatment Allegations by Child Characteristics - State



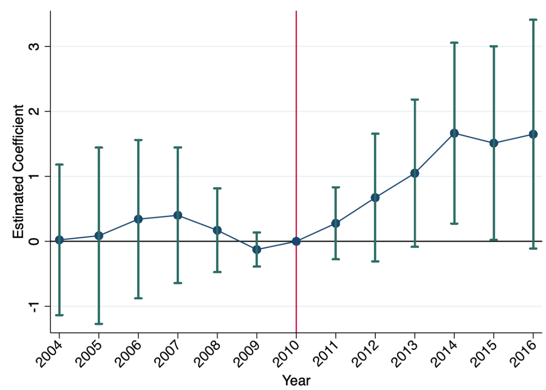
(a) White



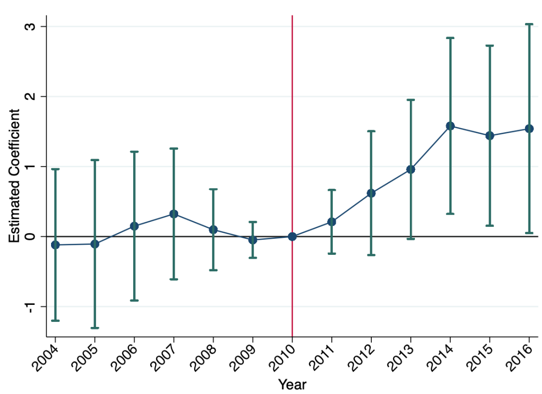
(b) Black



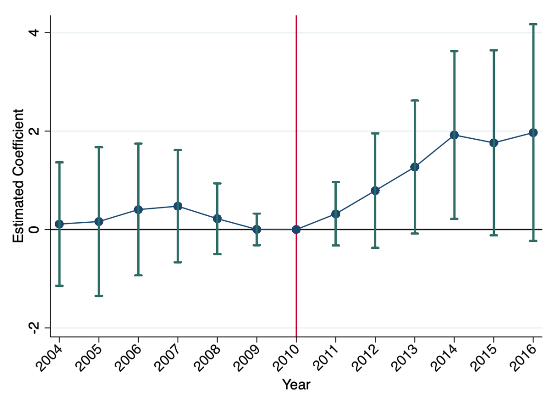
(c) Male



(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.

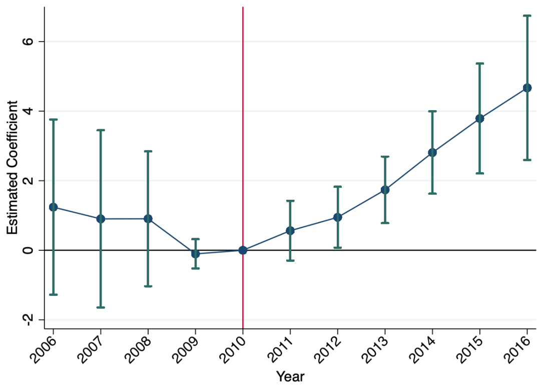
Table A5: Maltreatment Allegations by Child Characteristics - State

	(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)
	[4.4%]	[2.1%]	[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)
	[17.5%]	[7.5%]	[13.9%]	[13.1%]	[13.9%]	[13.8%]
Mean (2010)	13.834	6.047	11.882	11.975	10.582	13.271
Adjusted R^2	0.870	0.911	0.872	0.867	0.879	0.864
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

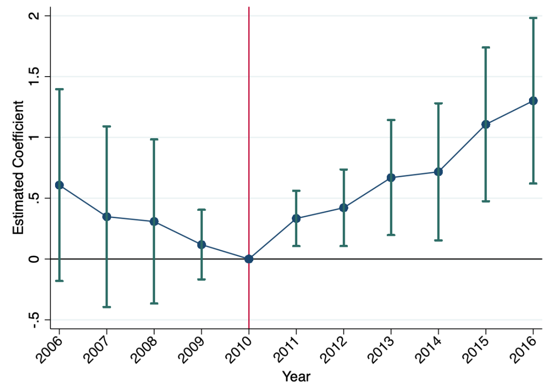
Notes. This table reports point estimates and standard errors from Equation 3, where the dependent variables are maltreatment allegations reported by professionals, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the 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 Child Charateristics - County

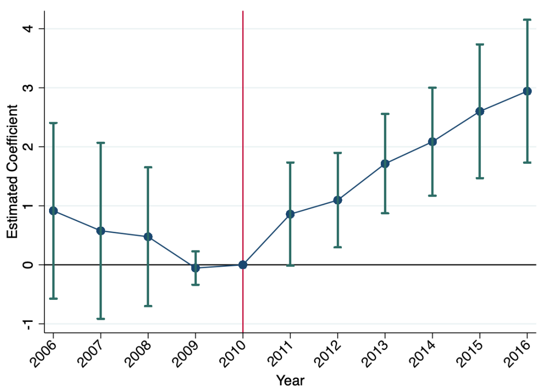
Figure A6: Maltreatment Allegations by Child Characteristics - County



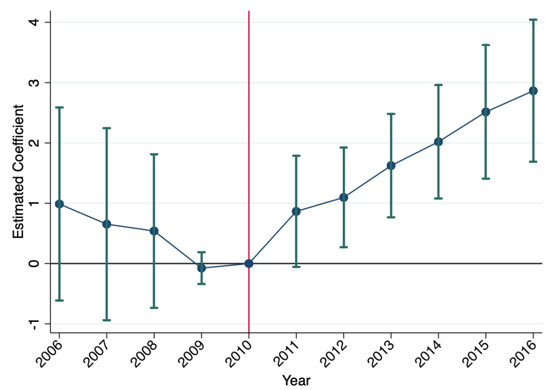
(a) White



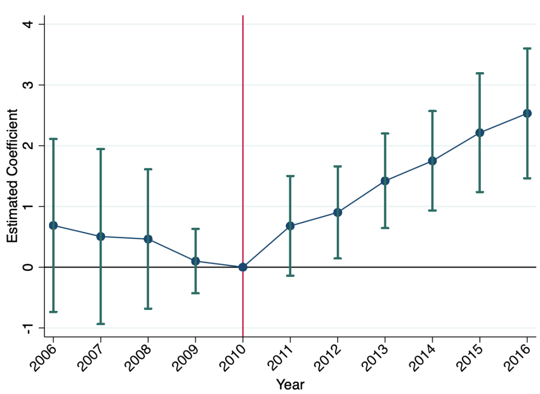
(b) Black



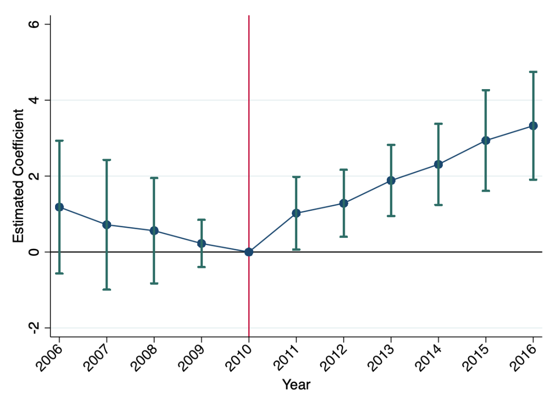
(c) Male



(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 2 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.

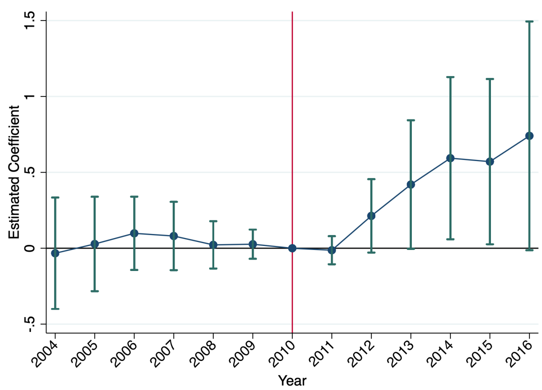
Table A6: Maltreatment Allegations by Child Characteristics - County

	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
Pre-reformulation	0.730	0.344	0.468	0.512	0.437	0.662
	(0.894)	(0.283)	(0.506)	(0.545)	(0.545)	(0.649)
Short-run	1.046***	0.459***	1.216***	1.190***	0.992**	1.389***
	(0.357)	(0.136)	(0.395)	(0.416)	(0.378)	(0.433)
	[7.6%]	[7.6%]	[10.2%]	[9.9%]	[9.4%]	[10.5%]
Medium-run	3.708***	1.016***	2.524***	2.452***	2.142***	2.835***
	(0.780)	(0.287)	(0.513)	(0.508)	(0.449)	(0.597)
	[26.8%]	[16.8%]	[21.2%]	[20.5%]	[20.2%]	[21.4%]
Mean (2010)	13.834	6.047	11.882	11.975	10.582	13.271
Adjusted R^2	0.887	0.912	0.859	0.855	0.868	0.846
Observations	6952	6952	7073	7073	7073	7073
α_s	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes	Yes

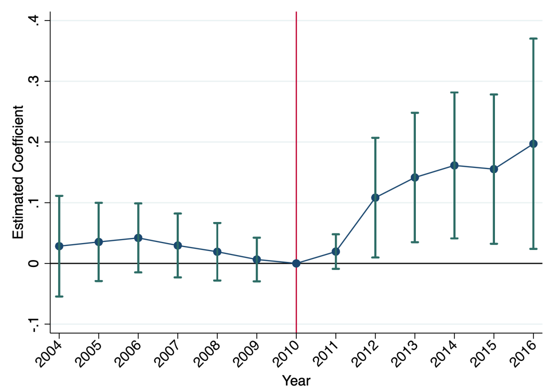
Notes. This table reports point estimates and standard errors from Equation 4, where the dependent variables are maltreatment allegations reported by professionals, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

G False Negatives by Maltreatment Types and Child Characteristics - State

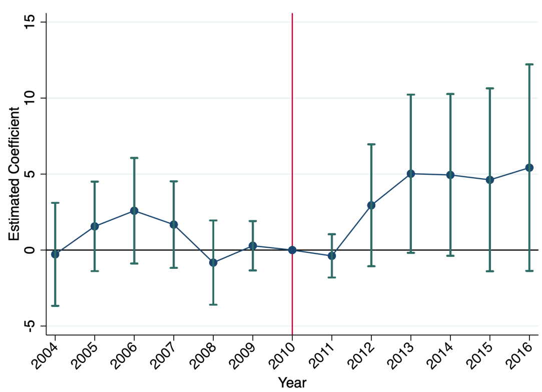
Figure A7: False Negative Rate by Maltreatment Type - State



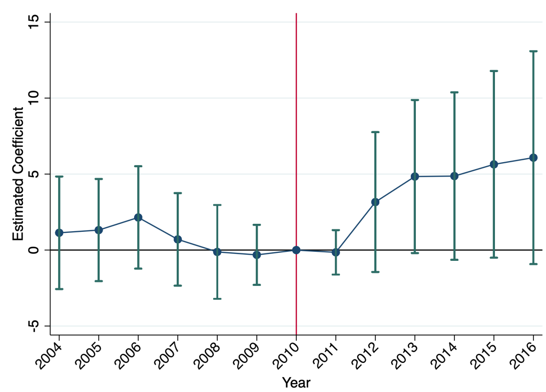
(a) Neglect, per 1,000 Children



(b) Physical Abuse, per 1,000 Children



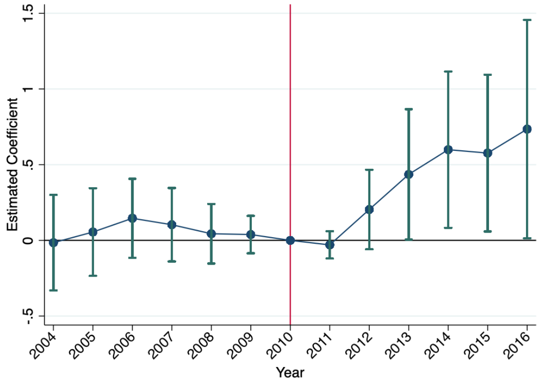
(c) Neglect, per 1,000 Allegations



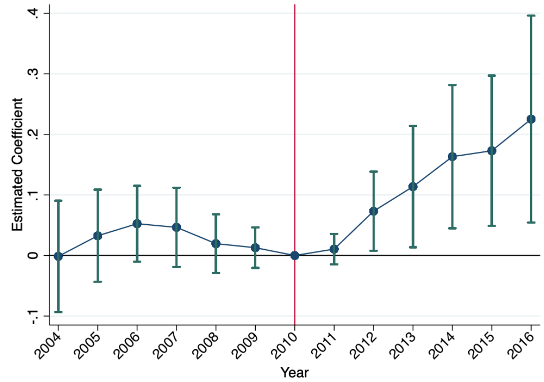
(d) Physical Abuse, per 1,000 Allegations

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 negative rates by maltreatment type. Regressions are weighted by child population.

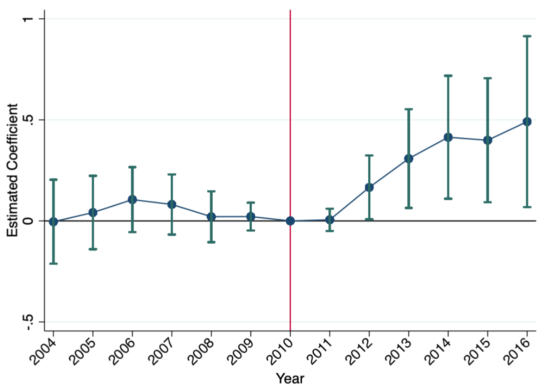
Figure A8: False Negatives per 1,000 Children by Child Characteristics - State



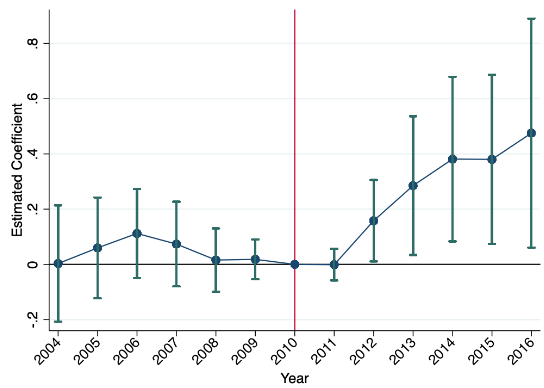
(a) White



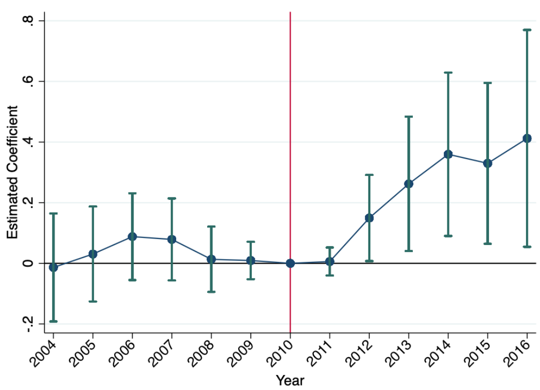
(b) Black



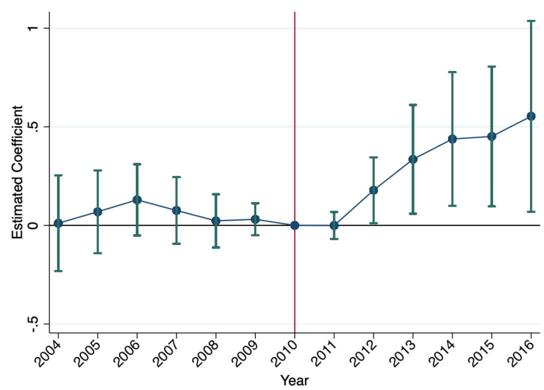
(c) Male



(d) Female



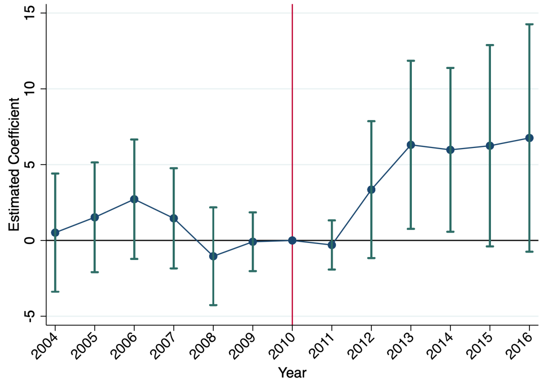
(e) Young



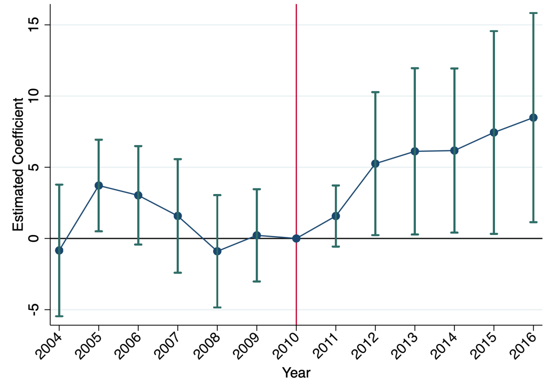
(f) Old

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.

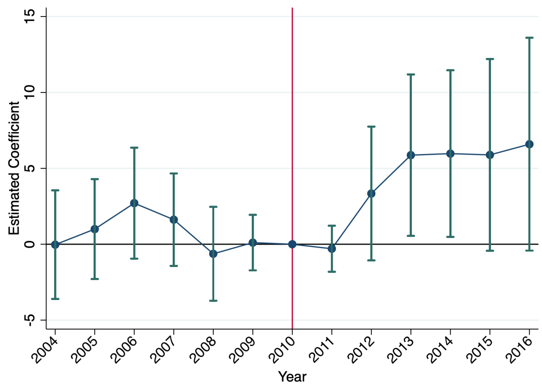
Figure A9: False Negatives per 1,000 Allegations by Child Characteristics - State



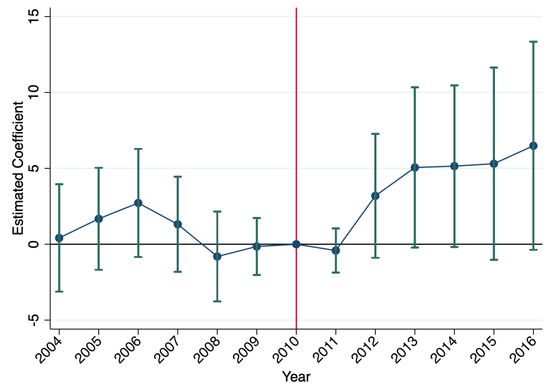
(a) White



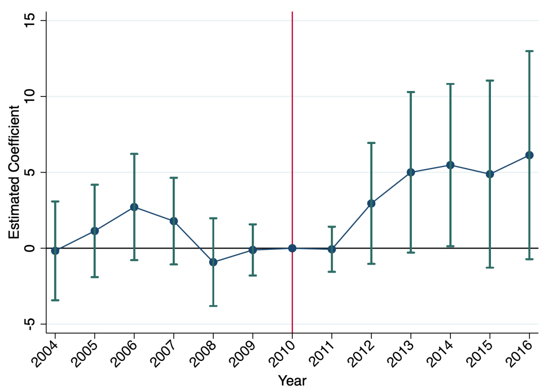
(b) Black



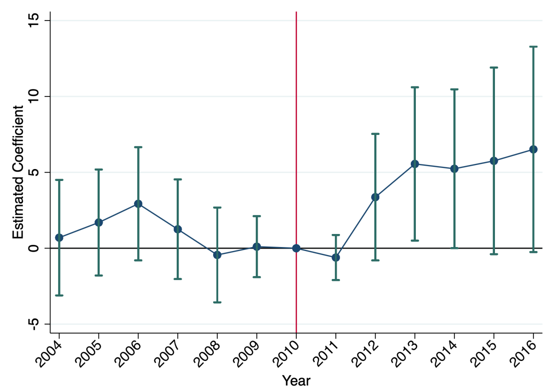
(c) Male



(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: False Negatives per 1K Children by Type and Child Characteristics - State

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.036	0.025	0.001	-0.001	0.000	-0.000	0.000	0.000
	(0.093)	(0.021)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Short-run	0.199*	0.088**	0.003**	0.005	0.004**	0.003*	0.003**	0.003**
	(0.105)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
	[14.1%]	[15.6%]	[0.6%]	[0.3%]	[0.3%]	[0.3%]	[0.3%]	[0.2%]
Medium-run	0.604**	0.164**	0.007**	0.007	0.007**	0.006**	0.006**	0.006**
	(0.288)	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
	[42.8%]	[29.0%]	[1.5%]	[0.5%]	[0.6%]	[0.5%]	[0.6%]	[0.5%]
Mean (2010)	1.411	0.565	0.471	1.477	1.169	1.177	1.07	1.277
Adjusted R^2	0.686	0.719	0.920	0.889	0.957	0.957	0.956	0.955
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 3, 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: False Negatives per 1K Allegations by Type and Child Characteristics - State

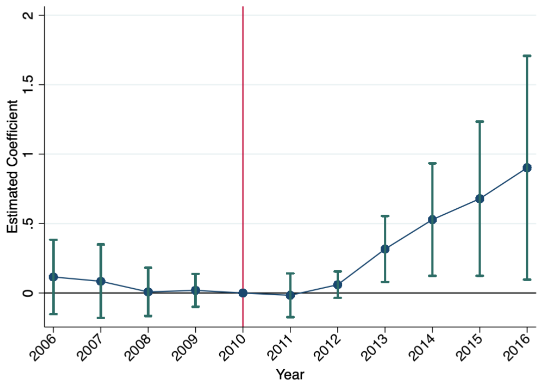
	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.744	0.657	0.706	1.044	0.714	0.721	0.639	0.909
	(1.079)	(1.246)	(1.336)	(1.492)	(1.251)	(1.206)	(1.106)	(1.326)
Short-run	2.468	2.548	3.034*	4.261**	2.893*	2.528	2.575	2.669*
	(1.604)	(1.692)	(1.752)	(1.929)	(1.683)	(1.649)	(1.654)	(1.569)
	[4.5%]	[4.5%]	[5.3%]	[7.2%]	[5.1%]	[4.5%]	[4.8%]	[4.5%]
Medium-run	4.684	5.238*	5.974*	7.082**	5.800*	5.304*	5.203*	5.461*
	(2.811)	(2.917)	(3.054)	(3.190)	(2.930)	(2.885)	(2.870)	(2.805)
	[8.6%]	[9.3%]	[10.5%]	[12.0%]	[10.2%]	[9.4%]	[9.6%]	[9.2%]
Mean (2010)	54.761	56.373	57.108	58.855	56.74	56.574	54.062	59.202
Adjusted R^2	0.774	0.746	0.781	0.747	0.785	0.782	0.787	0.775
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 3, 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.

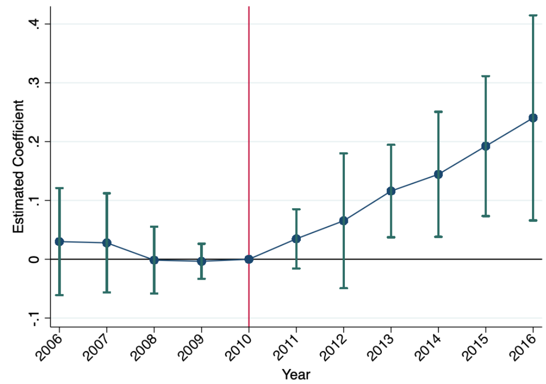
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

H False Negatives by Maltreatment Types and Child Characteristics - County

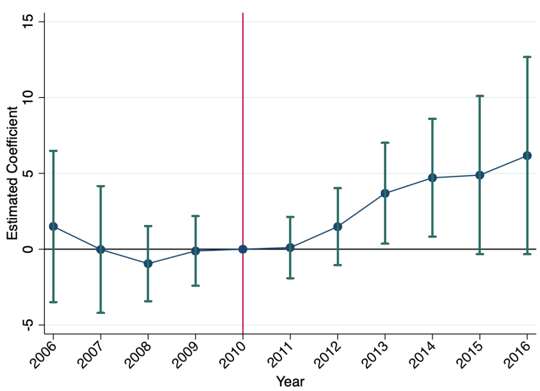
Figure A10: False Negative Rate by Maltreatment Type - County



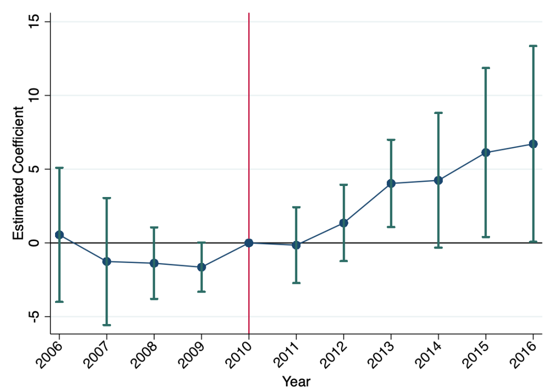
(a) Neglect, per 1,000 Children



(b) Physical Abuse, per 1,000 Children



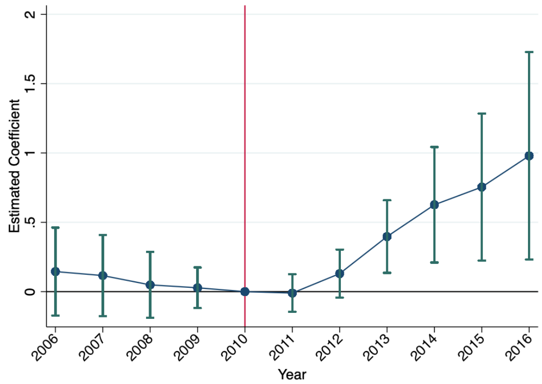
(c) Neglect, per 1,000 Allegations



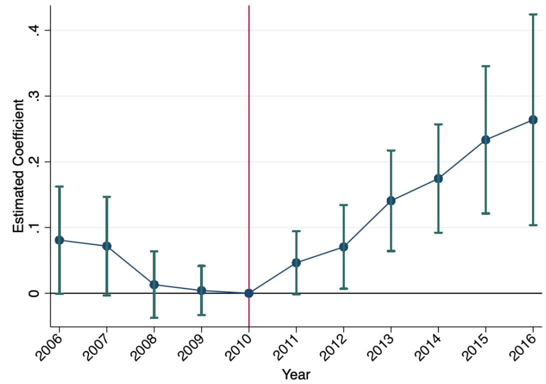
(d) Physical Abuse, per 1,000 Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 that are adjusted for within-state clustering. Dependent variables are false negative rates by maltreatment type. Regressions are weighted by child population.

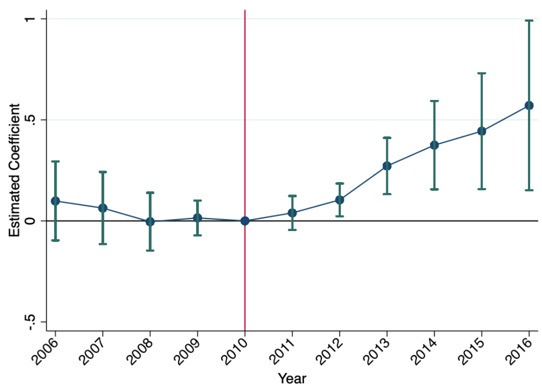
Figure A11: False Negatives per 1,000 Children by Child Characteristics - County



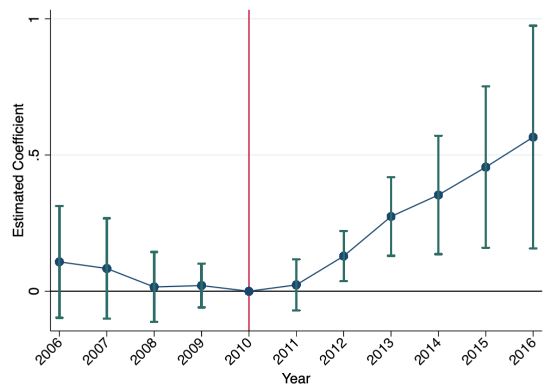
(a) White



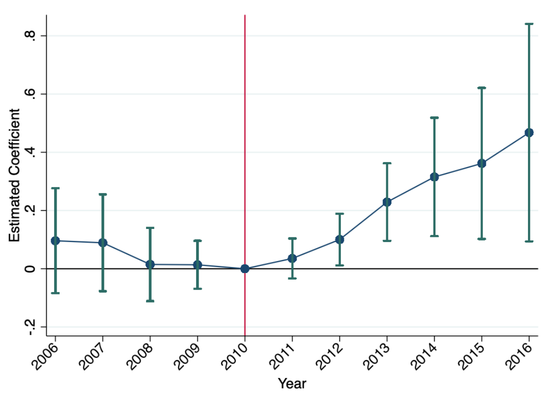
(b) Black



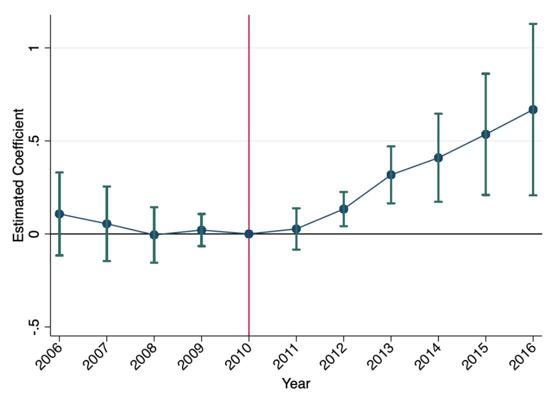
(c) Male



(d) Female



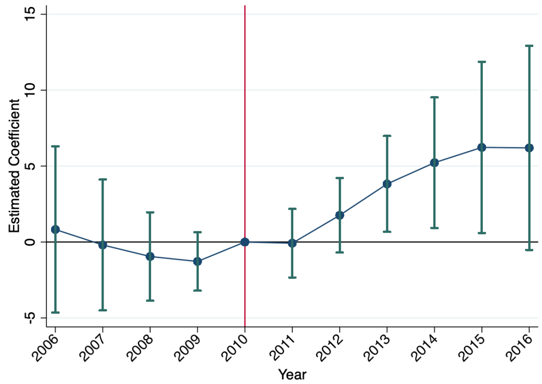
(e) Young



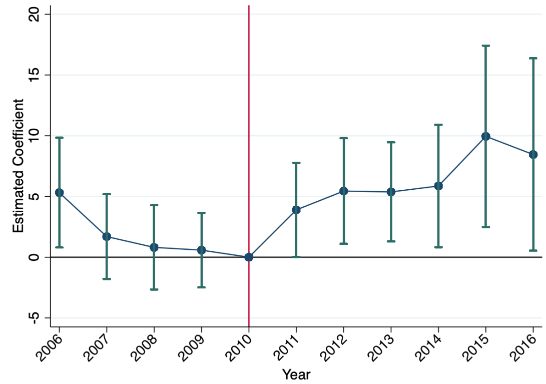
(f) Old

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 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.

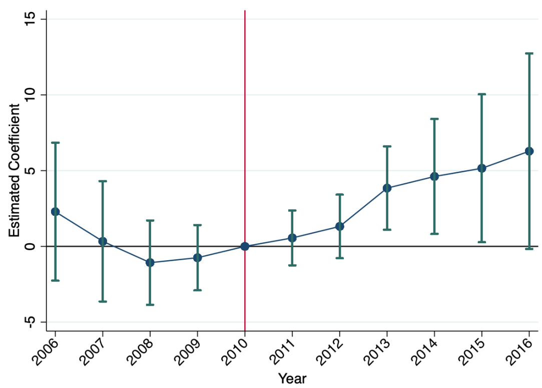
Figure A12: False Negatives per 1,000 Allegations by Child Characteristics - County



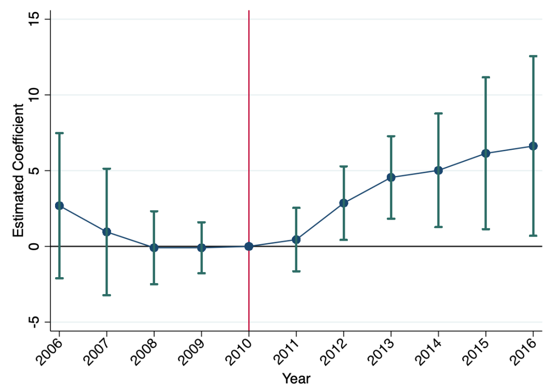
(a) White



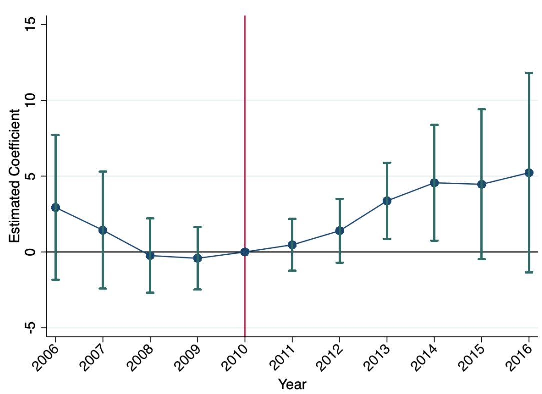
(b) Black



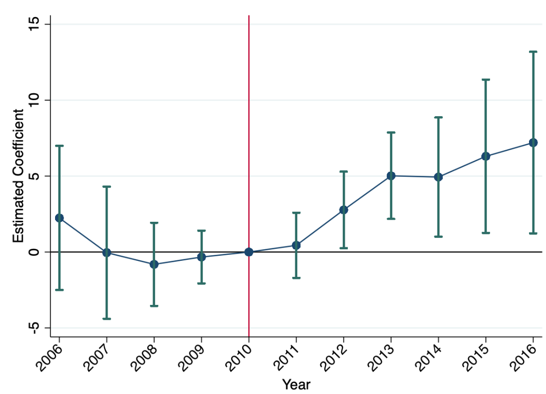
(c) Male



(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 2 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 A9: False Negatives per 1K Children by Type and Child Characteristics - County

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.058	0.013	0.012	0.069*	0.014	0.019	0.023	0.013
	(0.089)	(0.030)	(0.039)	(0.037)	(0.039)	(0.032)	(0.035)	(0.037)
Short-run	0.114**	0.071*	0.084**	0.151***	0.089***	0.077**	0.075**	0.089***
	(0.046)	(0.036)	(0.032)	(0.048)	(0.027)	(0.030)	(0.029)	(0.028)
	[8.1%]	[12.6%]	[17.8%]	[10.2%]	[7.6%]	[6.5%]	[7.0%]	[7.0%]
Medium-run	0.685**	0.188***	0.209***	0.294**	0.214***	0.199**	0.178**	0.220***
	(0.286)	(0.061)	(0.076)	(0.112)	(0.072)	(0.076)	(0.074)	(0.075)
	[48.5%]	[33.3%]	[44.4%]	[19.9%]	[18.3%]	[16.9%]	[16.6%]	[17.2%]
Mean (2010)	1.411	0.565	0.471	1.477	1.169	1.177	1.07	1.277
Adjusted R^2	0.689	0.670	0.895	0.590	0.892	0.891	0.887	0.888
Observations	4587	4587	4587	4587	4587	4587	4587	4587
α_c	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3, 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.

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

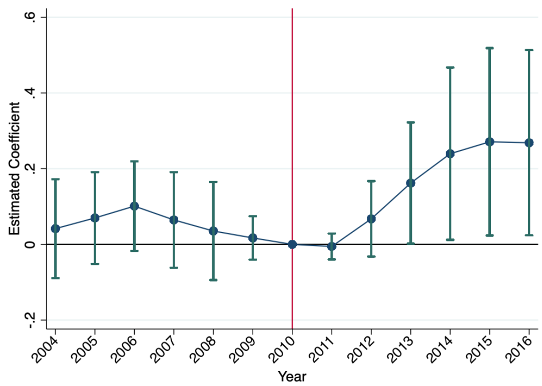
Table A10: False Negative Rate by Type and Child Characteristics - County

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.088	-0.946	-0.427	1.998*	0.145	0.826	0.855	0.239
	(1.488)	(1.215)	(1.540)	(1.175)	(1.399)	(1.379)	(1.312)	(1.475)
Short-run	1.710	1.685	1.782*	4.929***	1.887**	2.567***	1.735**	2.680***
	(1.069)	(1.105)	(1.010)	(1.478)	(0.813)	(0.943)	(0.797)	(0.954)
	[3.1%]	[3.0%]	[3.1%]	[8.4%]	[3.3%]	[4.5%]	[3.2%]	[4.5%]
Medium-run	5.124**	5.525**	5.759**	8.101**	5.274**	5.798**	4.715*	5.977**
	(2.449)	(2.676)	(2.555)	(3.266)	(2.377)	(2.321)	(2.428)	(2.353)
	[9.4%]	[9.8%]	[10.1%]	[13.8%]	[9.3%]	[10.2%]	[8.7%]	[10.1%]
Mean (2010)	54.761	56.373	57.108	58.855	56.74	56.574	54.062	59.202
Adjusted R^2	0.687	0.590	0.703	0.441	0.708	0.703	0.717	0.687
Observations	4587	4587	4587	4587	4587	4587	4587	4587
α_c	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

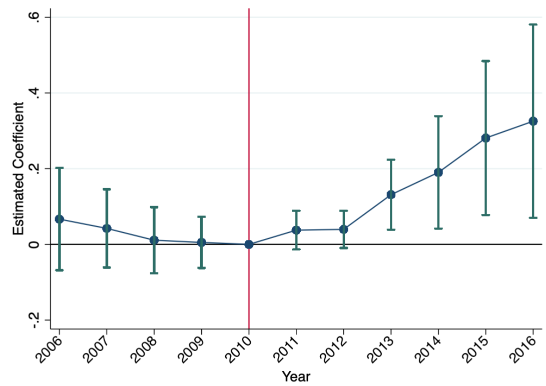
Notes. This table reports point estimates and standard errors from Equation 4, where the dependent variables are maltreatment allegations reported by professionals, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

I Alternative Measures of False Negatives

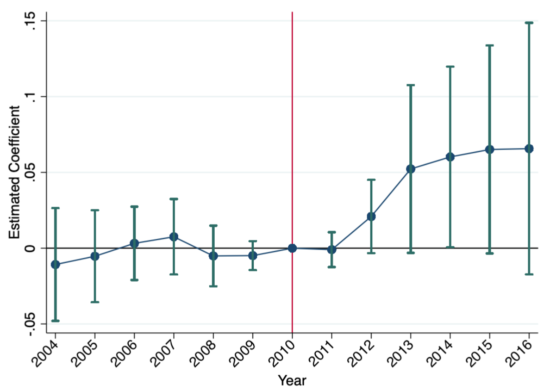
Figure A13: False Negatives per 1,000 Children - Alternative Measures



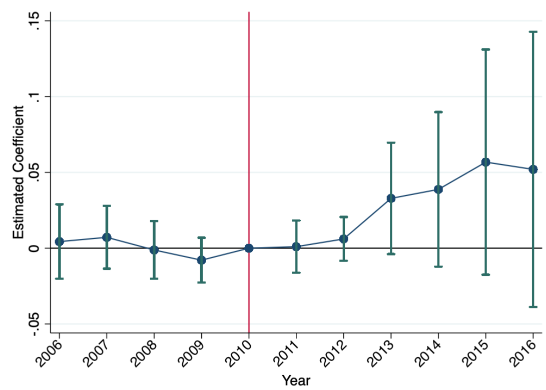
(a) State, Substantiation



(b) County, Substantiation



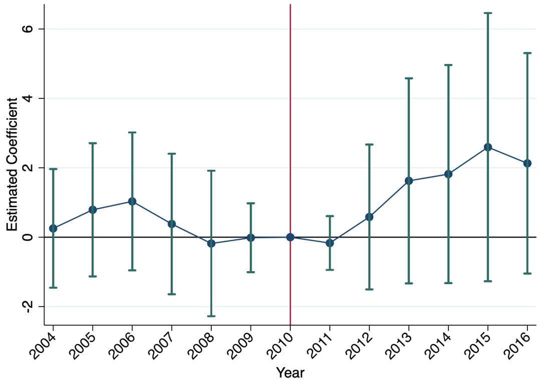
(c) State, Foster Care



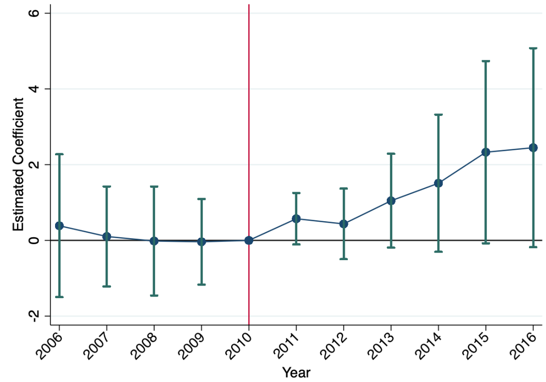
(d) County, Foster Care

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 and Equation 2 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.

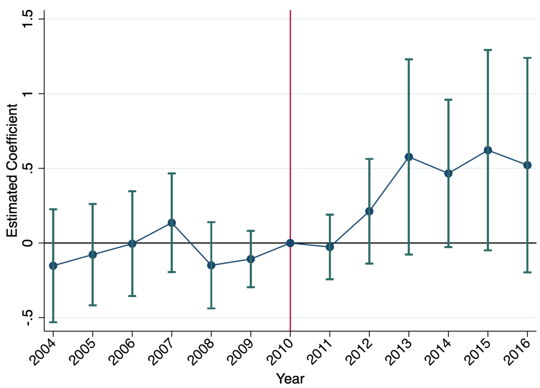
Figure A14: False Negatives per 1,000 Allegations - Alternative Measures



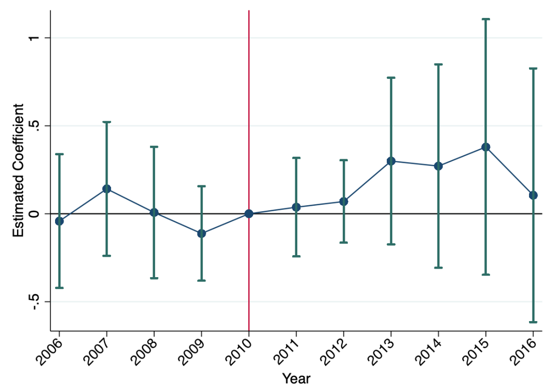
(a) State, Substantiation



(b) County, Substantiation



(c) State, Foster Care



(d) County, Foster Care

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 and Equation 2 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 A11: Difference-in-Differences Results for False Negatives per 1K Children by Alternative Measures

	(1) State Substantiation	(2) State Foster Care	(3) County Substantiation	(4) County Foster Care
Pre-reformulation	0.051	-0.003	0.031	0.001
	(0.052)	(0.010)	(0.045)	(0.007)
Short-run	0.072	0.023*	0.069***	0.013
	(0.045)	(0.014)	(0.023)	(0.008)
	[11.3%]	[14.8%]	[10.8%]	[8.4%]
Medium-run	0.249**	0.060*	0.261**	0.048
	(0.114)	(0.033)	(0.098)	(0.035)
	[39.0%]	[38.7%]	[40.9%]	[31.0%]
Mean (2010)	0.638	0.155	0.638	0.155
Adjusted R^2	0.786	0.644	0.739	0.560
Observations	506	506	4587	4587
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

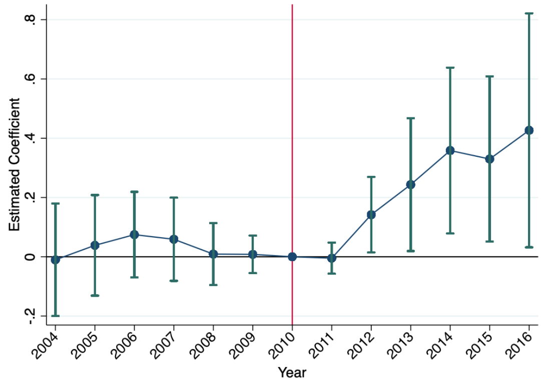
Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where The dependent variables are false negatives per 1,000 children by alternative measures. Columns (1) and (3) report the results for false negatives based on subsequent substantiation following the reports from professionals. Columns (2) and (4) report the results for false negatives based on subsequent foster care placements following the reports from professionals. Columns (1) and (2) are state-level results whereas Columns (3) and (4) are county-level results. 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 A12: Difference-in-Differences Results for False Negatives per 1K Allegations by Alternative Measures

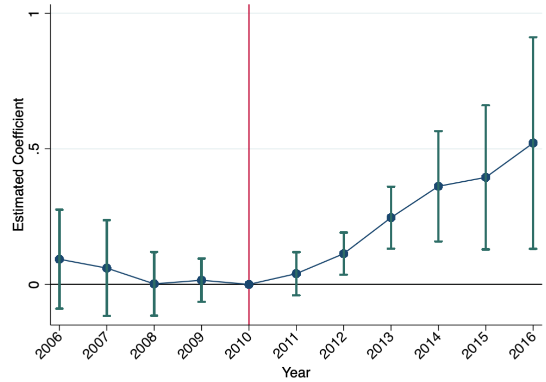
	(1) State Substantiation	(2) State Foster Care	(3) County Substantiation	(4) County Foster Care
Pre-reformulation	0.336	-0.059	0.105	-0.003
	(0.796)	(0.129)	(0.660)	(0.138)
Short-run	0.674	0.246	0.682*	0.133
	(0.927)	(0.179)	(0.363)	(0.132)
	[3.0%]	[6.6%]	[4.5%]	[3.6%]
Medium-run	2.090	0.496*	2.072*	0.248
	(1.617)	(0.286)	(1.092)	(0.310)
	[9.4%]	[13.3%]	[13.5%]	[6.7%]
Mean (2010)	15.301	3.726	15.301	3.726
Adjusted R^2	0.843	0.766	0.788	0.558
Observations	506	506	4587	4587
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where The dependent variables are false negatives per 1,000 allegations by alternative measures. Columns (1) and (3) report the results for false negatives based on subsequent substantiation following the reports from professionals. Columns (2) and (4) report the results for false negatives based on subsequent foster care placements following the reports from professionals. Columns (1) and (2) are state-level results whereas Columns (3) and (4) are county-level results. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

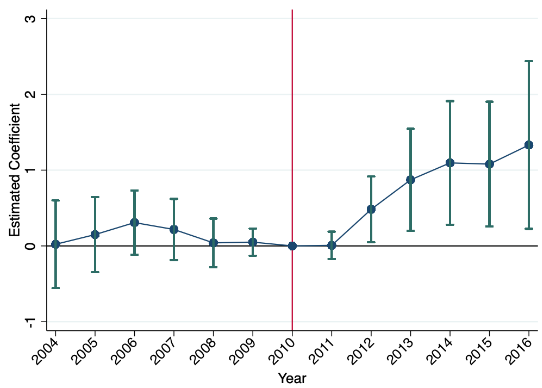
Figure A15: False Negatives per 1,000 Children - Alternative Time Frames



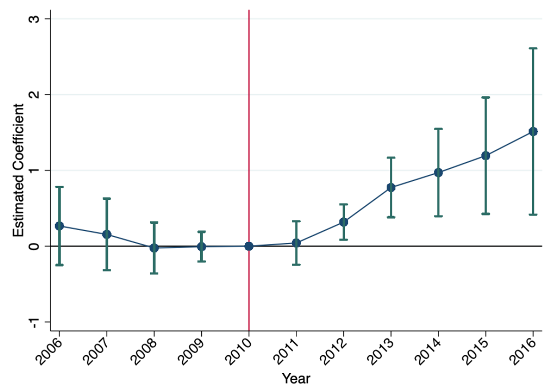
(a) State, 3 Months



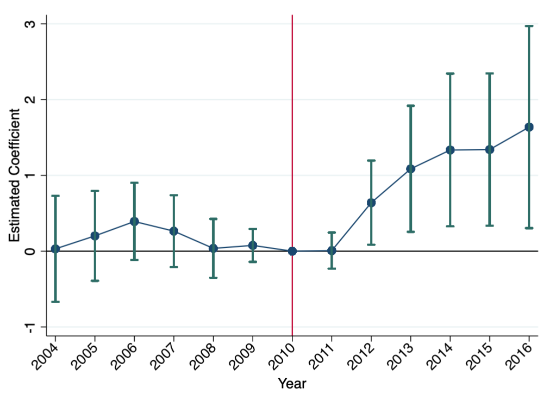
(b) County, 3 Months



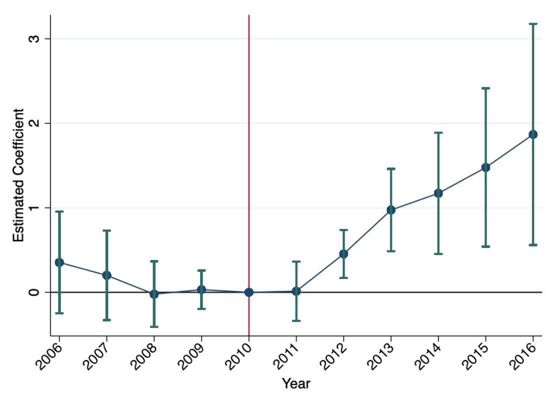
(c) State, 9 Months



(d) County, 9 Months



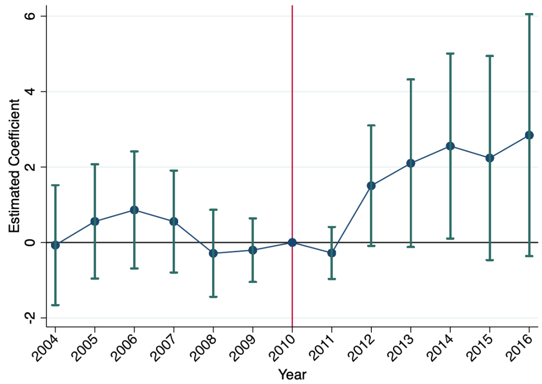
(e) State, 12 Months



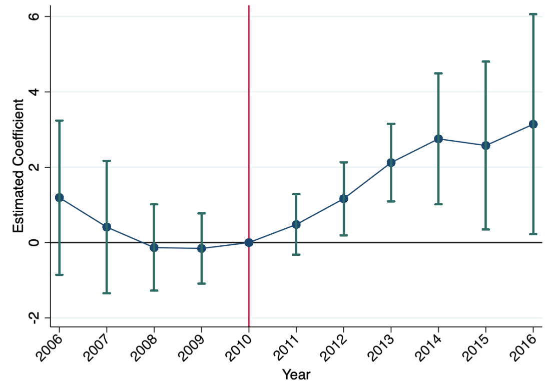
(f) County, 12 Months

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 and Equation 2 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.

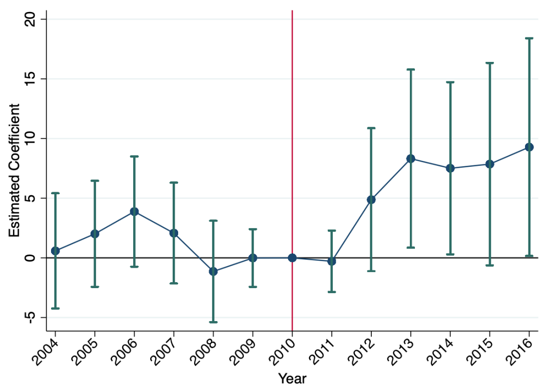
Figure A16: False Negatives per 1,000 Allegations - Alternative Time Frames



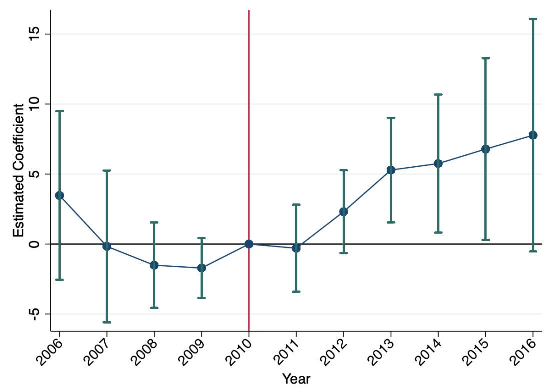
(a) State, 3 Months



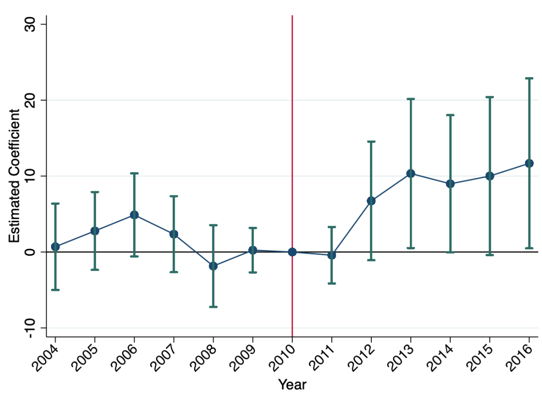
(b) County, 3 Months



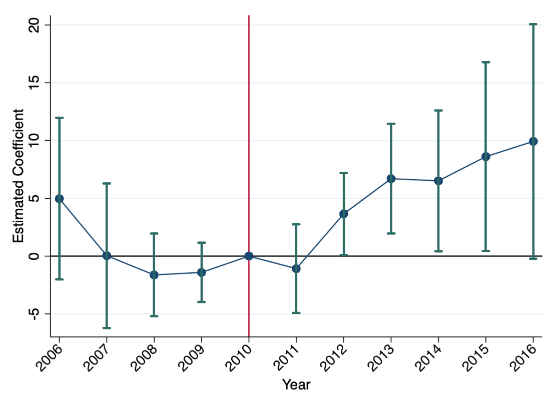
(c) State, 9 Months



(d) County, 9 Months



(e) State, 12 Months



(f) County, 12 Months

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 1 and Equation 2 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 A13: Difference-in-Differences Results for False Negatives per 1K Children by Time Frame

	(1) State 3 Months	(2) State 9 Months	(3) State 12 Months	(4) County 3 Months	(5) County 9 Months	(6) County 12 Months
Pre-reformulation	0.028	0.122	0.155	0.042	0.098	0.141
	(0.055)	(0.160)	(0.190)	(0.062)	(0.167)	(0.189)
Short-run	0.123**	0.440**	0.560**	0.130***	0.367***	0.464***
	(0.057)	(0.177)	(0.224)	(0.028)	(0.096)	(0.116)
	[13.3%]	[13.1%]	[13.2%]	[14.0%]	[10.9%]	[10.9%]
Medium-run	0.355**	1.110**	1.365**	0.416***	1.193***	1.460***
	(0.149)	(0.429)	(0.524)	(0.138)	(0.391)	(0.476)
	[38.3%]	[32.9%]	[32.1%]	[44.9%]	[35.4%]	[34.3%]
Mean (2010)	0.926	3.371	4.251	0.926	3.371	4.251
Adjusted R^2	0.705	0.739	0.745	0.675	0.722	0.731
Observations	506	506	506	4587	4587	4587
α_s or α_c	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

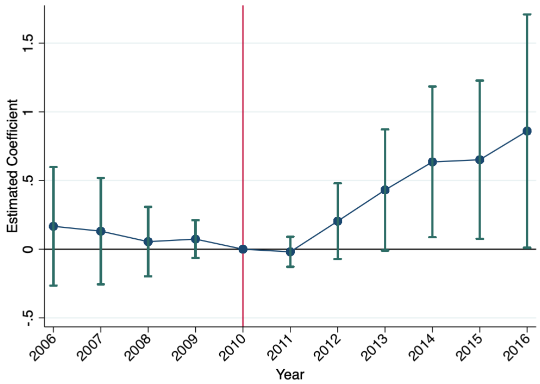
Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are false negatives per 1,000 children by the duration between the placement decision and re-referral. Columns (1), (2), and (3) are state-level results whereas Columns (4), (5), and (6) are county-level results. 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 A14: Difference-in-Differences Results for False Negatives per 1K Allegations by Time Frame

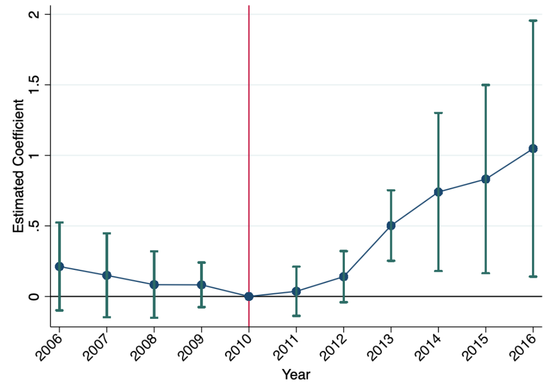
	(1) State 3 Months	(2) State 9 Months	(3) State 12 Months	(4) County 3 Months	(5) County 9 Months	(6) County 12 Months
Pre-reformulation	0.187	1.035	1.258	0.306	-0.068	0.394
	(0.533)	(1.656)	(1.951)	(0.588)	(1.662)	(1.858)
Short-run	1.076	4.180*	5.402	1.240***	2.384**	2.999**
	(0.668)	(2.411)	(3.262)	(0.354)	(1.174)	(1.421)
	[4.8%]	[5.2%]	[5.3%]	[5.6%]	[2.9%]	[2.9%]
Medium-run	2.400*	7.677*	9.540*	2.785**	6.634**	8.117**
	(1.302)	(3.877)	(4.808)	(1.092)	(3.102)	(3.869)
	[10.8%]	[9.5%]	[9.4%]	[12.5%]	[8.2%]	[8.0%]
Mean (2010)	22.199	80.852	101.949	22.199	80.852	101.949
Adjusted R^2	0.776	0.786	0.787	0.696	0.736	0.742
Observations	506	506	506	4587	4587	4587
α_s or α_c	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where The dependent variables are false negatives per 1,000 allegations by the duration between the placement decision and re-referral. Columns (1), (2), and (3) are state-level results whereas Columns (4), (5), and (6) are county-level results. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

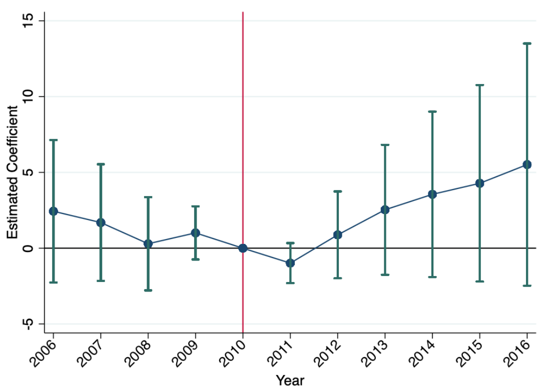
Figure A17: False Negative Rate Based on Service Provision



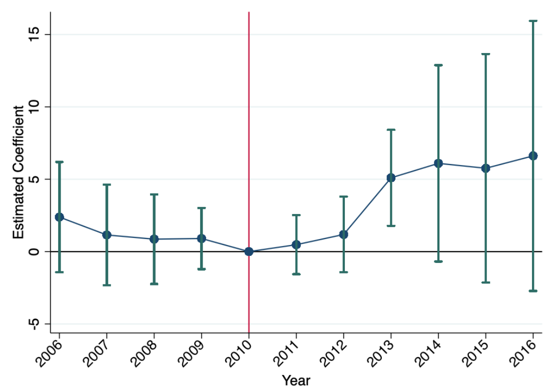
(a) FN by State, per 1,000 Children



(b) FN by County, per 1,000 Children



(c) FN by State, per 1,000 Allegations



(d) FN by County, 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 and Equation 2 that are adjusted for within-state clustering. Dependent variables are false negative rates based on service provision.

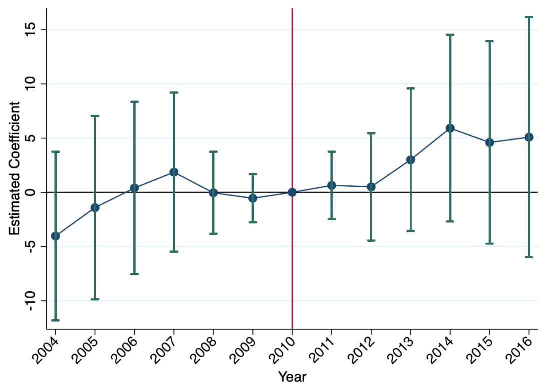
Table A15: Difference-in-Differences Results False Negative Rate Based on Service

	(1) FN Children State	(2) FN Children County	(3) FN Allegations State	(4) FN Allegations County
Pre-reformulation	0.088	0.133	0.918	1.321
	(0.108)	(0.115)	(1.232)	(1.434)
Short-run	0.185*	0.219***	0.742	2.187**
	(0.107)	(0.056)	(1.128)	(0.853)
	[11.0%]	[13.0%]	[1.8%]	[5.4%]
Medium-run	0.676**	0.851**	4.384	5.997
	(0.319)	(0.342)	(3.077)	(3.845)
	[40.1%]	[50.4%]	[10.8%]	[14.8%]
Mean (2010)	1.687	1.687	40.435	40.435
Adjusted R^2	0.651	0.655	0.662	0.67
Observations	492	4558	492	4558
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

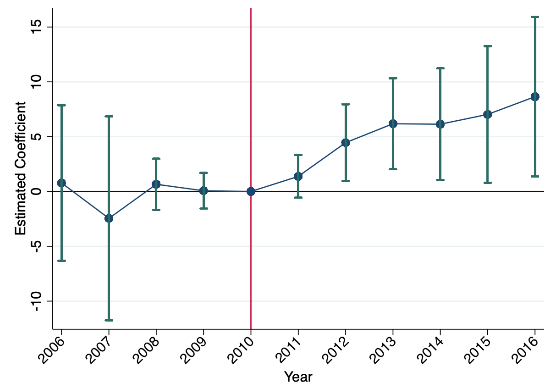
Notes. This table reports point estimates and standard errors from Equation 3 and 4, where the dependent variables are false negatives per 1,000 allegations based on service provision. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

J Binary Treatment

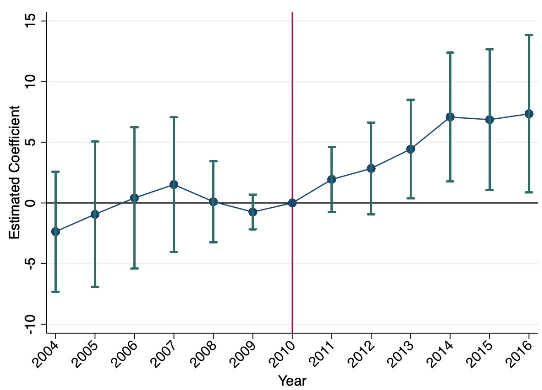
Figure A18: Event Study Results for Allegations per 1,000 Children - Binary Treatment



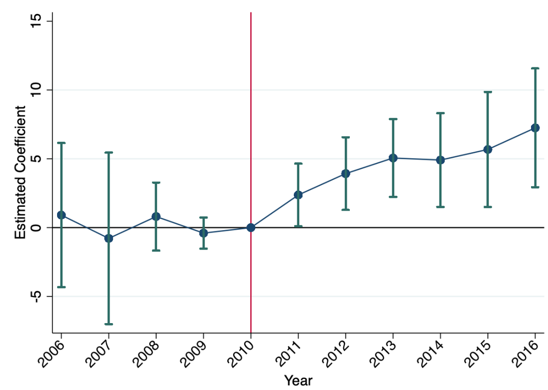
(a) Allegations by State



(b) Allegations by County



(c) Professional Allegations by State



(d) Professional Allegations by County

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 and Equation 2 that are adjusted for within-state clustering. The dependent variable is maltreatment allegations per 1,000 children. Figures (a) and (b) report results for all maltreatment allegations, while Figures (c) and (d) focus on allegations reported by professionals. Figures (a) and (c) are based on state-level analyses, whereas Figures (b) and (d) are based on county-level analyses. Regressions are weighted by child population.

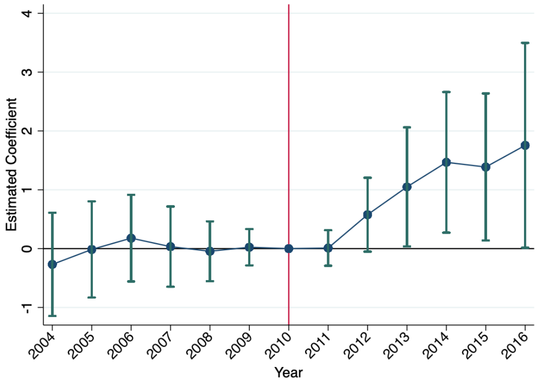
Table A16: Difference-in-Differences Results for Allegations per 1,000 Children - Binary Treatment

	(1) State All Allegations	(2) State Professional Allegations	(3) County All Allegations	(4) County Professional Allegations
Pre-reformulation	-0.529	-0.272	-0.203	0.131
	(2.598)	(2.002)	(2.182)	(1.658)
Short-run	1.366	3.045*	3.939***	3.746***
	(2.044)	(1.548)	(1.396)	(1.199)
	[3.1%]	[12.7%]	[9.0%]	[15.6%]
Medium-run	5.126	7.009**	7.136**	5.864***
	(4.766)	(2.872)	(3.070)	(1.965)
	[11.8%]	[29.2%]	[16.4%]	[24.5%]
Mean (2010)	43.609	23.976	43.609	23.976
Adjusted R^2	0.874	0.875	0.873	0.857
Observations	637	634	7073	7073
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

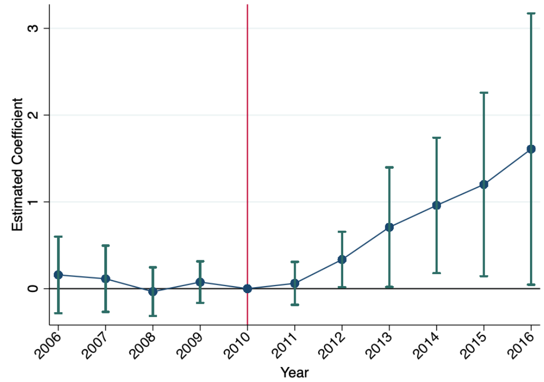
Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where The dependent variable is maltreatment allegations per 1,000 children. Columns (1) and (2) are based on a state-level analysis whereas Columns (3) and (4) are based on a county-level analysis. Columns (1) and (3) report the results for all allegations whereas Columns (2) and (4) report the results for allegations 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.

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

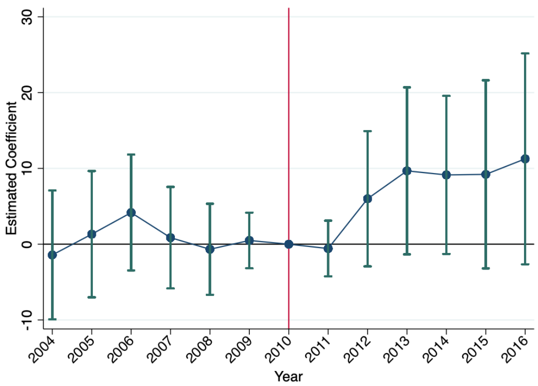
Figure A19: Event Study Results for False Negative Rates - Binary Treatment



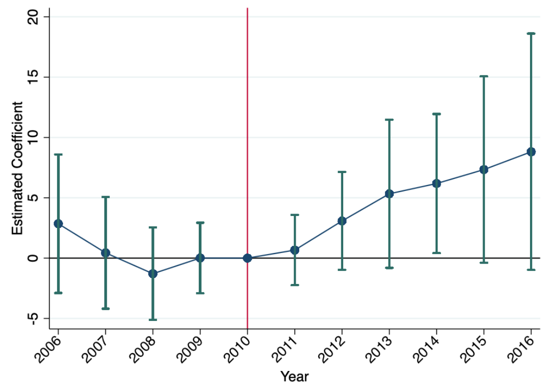
(a) FN by State, per 1,000 Children



(b) FN by County, per 1,000 Children



(c) FN by State, per 1,000 Allegations



(d) FN by County, 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 and Equation 2 that are adjusted for within-state clustering. The dependent variables are false negative rates. Regressions are weighted by child population.

Table A17: Difference-in-Differences Results for False Negative Rates - Binary Treatment

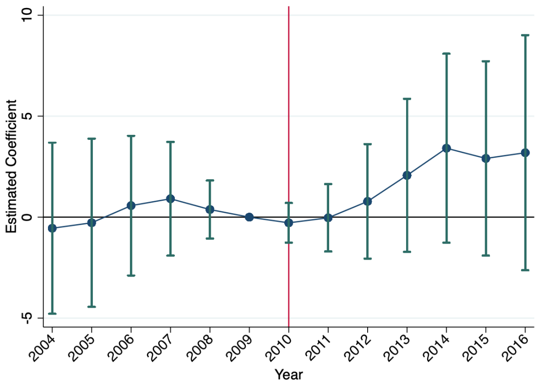
	(1) FN Children State	(2) FN Children County	(3) FN Allegations State	(4) FN Allegations County
Pre-reformulation	-0.017	0.082	0.710	0.485
	(0.281)	(0.143)	(2.855)	(1.794)
Short-run	0.539**	0.363**	4.971	3.003*
	(0.262)	(0.151)	(3.569)	(1.687)
	[22.9%]	[15.4%]	[8.8%]	[5.3%]
Medium-run	1.507**	1.238**	9.576	7.375*
	(0.676)	(0.559)	(5.900)	(3.755)
	[64.1%]	[52.7%]	[17.0%]	[13.1%]
Mean (2010)	2.35	2.35	56.373	56.373
Adjusted R^2	0.731	0.710	0.785	0.72
Observations	506	4587	506	4587
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are false negative rates. Columns (1) and (2) report the results for false negatives per 1,000 children whereas Columns (3) and (4) report the results for false negatives per 1,000 allegations. Columns (1) and (3) are based on a state-level analysis whereas Columns (2) and (4) are based on a county-level analysis. 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.

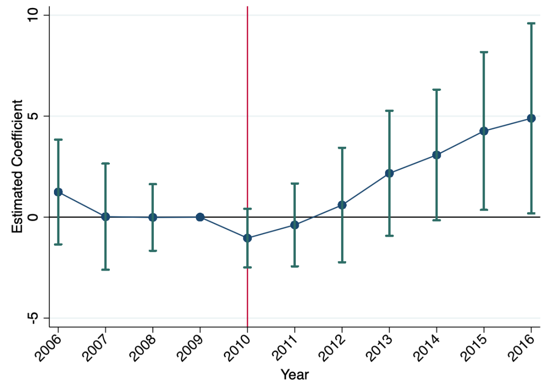
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

K Results for Year 2009 Normalized

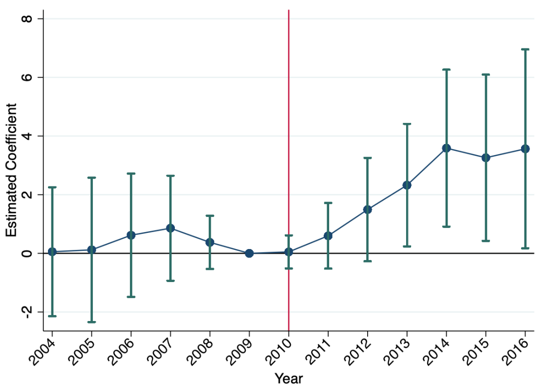
Figure A20: Event Study Results for Allegations per 1,000 Children - 2009 Normalized



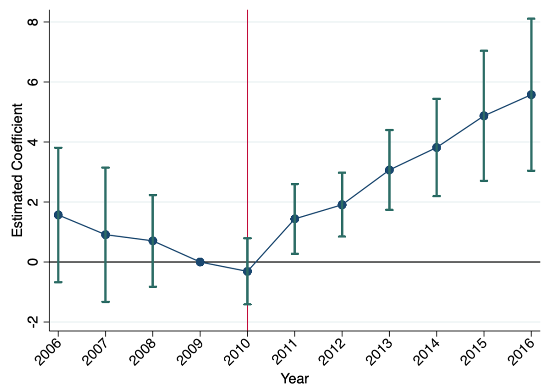
(a) Allegations by State



(b) Allegations by County



(c) Professional Allegations by State



(d) Professional Allegations by County

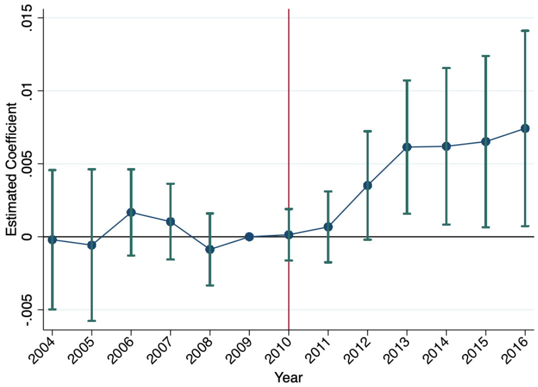
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 1 and Equation 2 that are adjusted for within-state clustering. The dependent variable is maltreatment allegations per 1,000 children. Figures (a) and (b) report results for all maltreatment allegations, while Figures (c) and (d) focus on allegations reported by professionals. Figures (a) and (c) are based on state-level analyses, whereas Figures (b) and (d) are based on county-level analyses. Regressions are weighted by child population.

Table A18: Difference-in-Differences Results for Allegations per 1,000 Children - 2009 Normalized

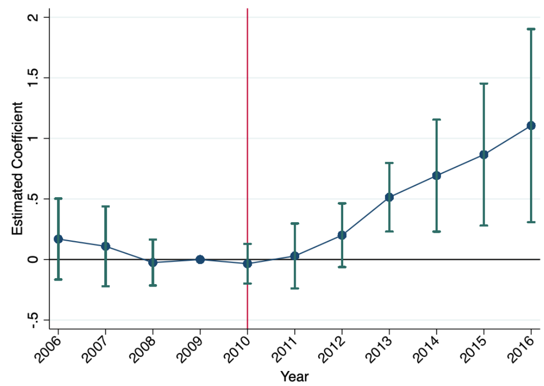
	(1) State All Allegations	(2) State Professional Allegations	(3) County All Allegations	(4) County Professional Allegations
Pre-reformulation	0.255	0.435	0.441	1.089
	(1.456)	(0.855)	(0.949)	(0.937)
Short-run	0.140	0.697*	-0.295	0.988***
	(0.702)	(0.393)	(1.000)	(0.342)
	[0.3%]	[2.9%]	[-0.7%]	[4.2%]
Medium-run	2.761	3.051**	3.460*	4.175***
	(2.218)	(1.247)	(1.761)	(0.861)
	[6.4%]	[12.9%]	[8.0%]	[17.6%]
Mean (2010)	43.068	23.661	43.068	23.661
Adjusted R^2	0.874	0.871	0.872	0.857
Observations	637	634	7073	7073
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where The dependent variable is maltreatment allegations per 1,000 children. Columns (1) and (2) are based on a state-level analysis whereas Columns (3) and (4) are based on a county-level analysis. Columns (1) and (3) report the results for all allegations whereas Columns (2) and (4) report the results for allegations 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

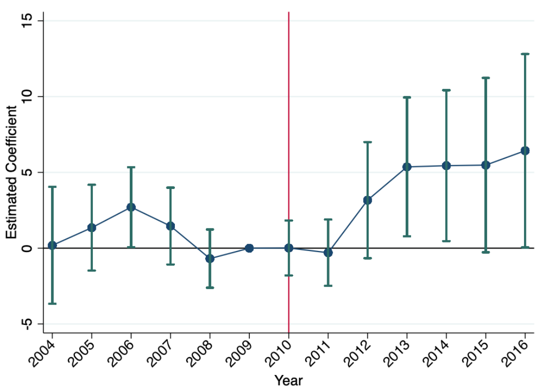
Figure A21: Event Study Results for False Negative Rates - 2009 Normalized



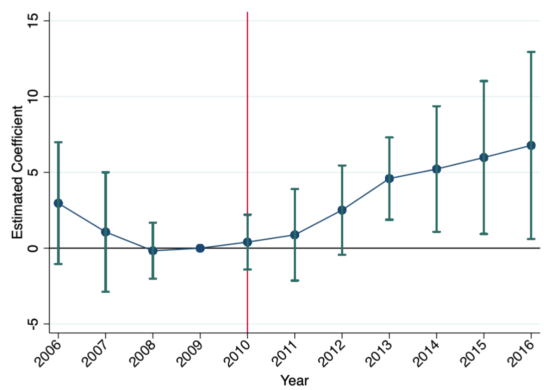
(a) FN by State, per 1,000 Children



(b) FN by County, per 1,000 Children



(c) FN by State, per 1,000 Allegations



(d) FN by County, 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 and Equation 2 that are adjusted for within-state clustering. The dependent variables are false negative rates. Regressions are weighted by child population.

Table A19: Difference-in-Differences Results for Placement and False Negative Rates

	(1) FN Children State	(2) FN Children County	(3) FN Allegations State	(4) FN Allegations County
Pre-reformulation	0.087	0.098	0.699	0.515
	(0.119)	(0.134)	(1.202)	(1.344)
Short-run	0.301**	0.275***	2.651	2.223**
	(0.129)	(0.066)	(1.600)	(0.839)
	[12.9%]	[11.8%]	[4.7%]	[3.9%]
Medium-run	0.809**	0.899***	5.415*	5.490**
	(0.321)	(0.295)	(2.831)	(2.308)
	[34.7%]	[38.6%]	[9.6%]	[9.7%]
Mean (2009)	2.33	2.33	56.547	56.547
Adjusted R^2	0.731	0.710	0.787	0.727
Observations	506	4587	506	4587
α_s or α_c	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 3 and Equation 4, where the dependent variables are false negative rates. Columns (1) and (2) report the results for false negatives per 1,000 children whereas Columns (3) and (4) report the results for false negatives per 1,000 allegations. Columns (1) and (3) are based on a state-level analysis whereas Columns (2) and (4) are based on a county-level analysis. 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 Heterogeneity Analysis for Placements - State

Table A20: Placement Rate by Type and Child Characteristics - State

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	-2.125	-0.586	-0.070	1.529	0.376	0.350	0.365	0.549
	(3.470)	(2.369)	(1.826)	(2.220)	(1.661)	(1.677)	(1.923)	(1.538)
Short-run	0.220	2.581	1.887	2.394	1.044	1.037	1.527	0.717
	(2.097)	(2.262)	(1.665)	(2.259)	(1.569)	(1.436)	(1.542)	(1.470)
	[0.3%]	[5.0%]	[3.3%]	[3.8%]	[1.9%]	[1.8%]	[2.2%]	[1.6%]
Medium-run	0.300	2.870	0.181	1.412	0.658	1.002	1.203	0.632
	(3.690)	(3.603)	(3.652)	(3.780)	(3.015)	(2.989)	(3.070)	(2.989)
	[0.4%]	[5.6%]	[0.3%]	[2.2%]	[1.2%]	[1.8%]	[1.8%]	[1.4%]
Mean (2010)	75.111	51.209	57.384	63.455	56.229	56.798	68.238	45.637
Adjusted R^2	0.879	0.832	0.781	0.782	0.756	0.762	0.769	0.753
Observations	559	559	559	559	559	559	559	559
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 3, where the dependent variables are foster care placements ber 1,000 allegations, 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

M Heterogeneity Analysis for Placements - County

Table A21: Placement Rate by Type and Child Characteristics - County

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	-4.389	-2.114	-2.881	-2.322	-1.544	-1.224	-3.079	-0.123
	(2.950)	(2.865)	(1.822)	(2.385)	(1.720)	(1.785)	(1.952)	(1.641)
Short-run	-0.514	1.593	2.455	1.184	-0.755	-0.468	-1.089	0.110
	(1.978)	(2.634)	(1.954)	(2.416)	(1.188)	(1.135)	(1.334)	(1.197)
	[-0.7%]	[3.1%]	[4.3%]	[1.9%]	[-1.3%]	[-0.8%]	[-1.6%]	[0.2%]
Medium-run	-6.199	-1.562	-0.793	-0.560	-2.842	-2.248	-3.784	-1.126
	(4.579)	(5.146)	(4.107)	(4.871)	(2.847)	(3.031)	(2.752)	(3.270)
	[-8.3%]	[-3.1%]	[-1.4%]	[-0.9%]	[-5.1%]	[-4.0%]	[-5.5%]	[-2.5%]
Mean (2010)	75.111	51.209	57.384	63.455	56.229	56.798	68.238	45.637
Adjusted R^2	0.840	0.788	0.749	0.620	0.731	0.739	0.744	0.722
Observations	5544	5544	5544	5544	5544	5544	5544	5544
α_c	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
γ_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 4, where the dependent variables are foster care placements per 1,000 allegations, 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

N Policy Variables

Table A22: Must-Access PDMPs and Medicaid Expansion

Year	PDMP	Medicaid
2006	NV	
2010	OK	
2011	OH	
2012	DE, KY, NM, WV	
2013	MA, NY, TN, VT	
2014	IN, LA	AZ, AR, CA, CO, CT, HI, IL, IA, KY, MD, MI, NV, NH, NJ, OH, RI, WA, WV
2015	CT, NJ, VA	PA, IN, AK
2016	NH, RI	MT, LA

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