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

Jeongsoo Suh*

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Abstract

This paper examines the impacts of the opioid epidemic on child maltreatment and how Child Protective Services (CPS) responded to the epidemic. I use the reformulation of OxyContin, a nationwide supply shock in prescription opioids that exacerbated the opioid epidemic, as a natural experiment. Leveraging variation in states' and counties' exposure to this intervention, I find that the opioid epidemic led to an increase in maltreatment allegations, suggesting a rise in the underlying maltreatment risk. Despite heightened risk, institutional responses did not scale protective actions accordingly, resulting in more cases where children were left at home but subsequently reinvestigated for maltreatment. Foster care placement rates remained unchanged and administrative expenditures per allegation declined, pointing to a limited systemic response. This study underscores the intergenerational consequences of the opioid epidemic and highlights how public health crises can weaken protective systems, particularly when institutions lack the flexibility or capacity to adapt.

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

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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. The opioid epidemic, referring to the sharp rise in opioid misuse, addiction, and overdose deaths in the United States since the late 1990s, is one of the most widespread and devastating public health crises. Since 1999, it has claimed nearly 727,000 lives (CDC, 2023). The opioid overdose death rate rose from 2.9 per 100,000 people in 1999 to 25.0 per 100,000 in 2022 (NCHS, 2023). This unprecedented rise in overdose deaths led the Centers for Disease Control and Prevention (CDC) to declare it the worst drug overdose crisis in U.S. history (Kolodny et al., 2015).

This paper examines the impacts of the opioid epidemic on child maltreatment and how Child Protective Services (CPS) responded to this crisis. 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). Child maltreatment is associated with a host of long-lasting consequences including lower educational attainment, reduced earnings, lower employment, fewer assets (Currie and Spatz Widom, 2010), and higher involvement in crime (Currie and Tekin, 2012) and substance use later in life (Cicchetti and Handley, 2019).

CPS plays a critical role in ensuring children's safety by investigating maltreatment allegations and placing endangered children in foster care, a state-supervised living arrangement that provides temporary care outside the home. However, during the opioid epidemic, changes in foster care placements were stagnant (Gihleb, Giuntella and Zhang, 2022) despite rising maltreatment allegations (Evans, Harris and Kessler, 2022). These trends raise questions about the extent of protection provided to children exposed to maltreatment risk during the epidemic.

I use the reformulation of OxyContin in 2010 as a natural experiment, a nationwide supply-side drug policy which has received extensive attention from both academics and the media due to its unintended consequences. This policy aimed to reduce OxyContin abuse by introducing an abuse-deterrent version of the original formulation. However, it inadvertently exacerbated the opioid epidemic by driving users toward illicit, more addictive substances including heroin and synthetic opioids, resulting in a substantial growth of the illicit drug market. As a result, the reformulation led to higher rates of opioid overdoses

(Powell and Pacula, 2021), heroin overdoses (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019), homicides (Tan, 2024), and heroin-related arrests (Park, 2022).

The identification strategy follows an exposure design, akin to Bartik or shift–share approaches, and leverages variation in states' and counties' differential exposure to the reformulation of OxyContin. Regions with higher rates of OxyContin misuse and greater prevalence of high-risk prescription opioids prior to the reformulation were more affected by the intervention. This is supported by the first stage results showing that areas with higher pre-reformulation OxyContin misuse rates and Schedule II prescription opioids per capita experienced greater declines in OxyContin misuse rates following the intervention, suggesting that the supply disruption had more "bite" in these regions. I use event study and difference-in-differences frameworks to compare outcome trends between regions with higher and lower exposure to the reformulation, estimating intent-to-treat (ITT) effect of the reformulation.

I use rich national administrative data that provide child-level information on child maltreatment cases reported to CPS. These data include child IDs that allow tracking of reinvestigations following initial investigations. To analyze the mechanism for CPS responses, I use the Child Welfare Financing Surveys, which report state expenditures on child protection. I aggregate these data to the county and state levels and merge them with measures of prescription opioids and OxyContin misuse from the CDC and Alpert, Powell and Pacula (2018).

I find that despite heightened risk driven by the opioid epidemic, institutional responses did not adjust accordingly, leaving more children in potentially harmful home environments without adequate protection. The opioid epidemic led to a rise in maltreatment allegations in states and counties more exposed to the reformulation of OxyContin, relative to less exposed regions. At the same time, it also led to an increase in the instances where CPS left children at home without protection, but they were subsequently reinvestigated for maltreatment. Because policy manuals for CPS investigators state that children should be placed in foster care when they are at risk of maltreatment at home, these findings point to a rise in false negatives, cases in which CPS did not place endangered children in foster care. Foster care placement rates remained flat and administrative expenditures per allegation declined, pointing to a limited systemic response.

A one standard deviation increase in exposure to the reformulation of OxyContin led to a 6 and 11 percent increase in maltreatment allegations per 10,000 children immediately following the reformulation at the state and county levels, respectively. In the subsequent years, these effects grew to 14 and 23 percent, corresponding to roughly 33 to 54 additional allegations per 10,000 children. In aggregate terms, these changes amount to approximately 798,000 to 1.3 million additional allegations nationwide. The magnitudes of these effects are equivalent to one-quarter of the Black–White gap in allegations per 10,000 children prior to the reformulation. These findings indicate that the reformulation heightened maltreatment risk by altering parental behavior through unintended consequences documented in the literature. In particular, increasing use of illicit drugs and the experience of withdrawal symptoms would have intensified stress, instability, and impaired caregiving capacity, raising the risk of child maltreatment.

An increase in the reinvestigations of children who were not initially placed in foster care indicates that a significant number of children exposed to maltreatment risk during the opioid epidemic were not protected by the system. Reinvestigations of maltreatment cases are a widely used proxy for subsequent maltreatment in the child welfare literature and serves as a quality metric among policymakers (Antle et al., 2009; Putnam-Hornstein et al., 2015; Putnam-Hornstein, Prindle and Hammond, 2021; Baron et al., 2024*a*,*b*). These cases represent false negatives, instances where children at risk of subsequent maltreatment were left at home without protection. I find that false negatives per 10,000 children increased by 12 to 14 percent immediately following the reformulation at the state and county levels, respectively. Over the subsequent three years, the effects grew to 37 and 42 percent. These estimates imply that roughly 45,000–50,000 at-risk children in the short run and 130,000–150,000 in the medium run were left at home without protection nationwide.

I further show that false negatives increased conditional on the number of allegations, that is, per 1,000 allegations. These results suggest that a larger share of allegations resulted in missed maltreatment cases following the reformulation. A one standard deviation increase in exposure to the reformulation yields a 5 and 4 percent increase in false negatives per 1,000 allegations at the state and county levels, respectively. In the subsequent years, the estimated effects were 8 and 10 percent.

As a mechanism for rising false negatives, I find that foster care placements per 1,000 allegations remained flat following the reformulation of OxyContin. This indicates that CPS maintained a relatively fixed placement rate, rather than adjusting placement rates in response to changes in underlying risk. Taken together with the increase in false negatives, these results suggest that CPS continued handling allegations as they had prior to the reformulation, despite the growing share of at-risk children.

The effectiveness and timeliness of CPS responses are closely tied to the level of expenditures by child welfare agencies. Insufficient fiscal responses to protect vulnerable children during the opioid epidemic have been raised by the media and widely discussed in public discourse. I find that child welfare agency expenditures from federal sources declined by 8 percent on a per-allegation basis following the reformulation. Foster care administrative expenditures, which include costs related to caseworker salaries, staff training, and case planning, fell by 15 percent. These findings suggest that fewer resources were allocated to each investigation, which in turn reduced CPS's capacity and ability to respond to heightened maltreatment risk during the opioid epidemic.

In addition, 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. I show this 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. Because congregate care is typically used only when foster homes are unavailable, trends in congregate placements per 1,000 allegations can serve as an indirect indicator of whether the supply of foster homes scaled with the increase in allegations. I find that the congregate placement rate remained stable before and after the reformulation, suggesting that the limited CPS response to heightened risk was not primarily due to foster home shortages.

This paper makes several contributions to the literature. First, it reconciles seemingly conflicting findings on the effects of the opioid epidemic on child welfare. Studies have documented a variety of socioeconomic consequences of the epidemic, including 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, Evans, Harris and Kessler (2022) documented the rise in maltreatment allegations whereas Gihleb, Giuntella and Zhang (2022) found stagnant changes in foster care placements. The absence of a unifying empirical analysis has made it difficult to reconcile these findings. By tracing the subsequent outcomes of the initial investigations, this paper provides empirical evidence that more at-risk children were left at home during the opioid epidemic, suggesting that the protective actions by CPS did not keep pace with rising risk. Furthermore, by examining the impact of the epidemic on children, this paper highlights its potential to generate intergenerational consequences, which may lead to long-term declines in mobility and widening socioeconomic inequality.

Second, this paper contributes to the literature on supply-side drug policies by examining not only the effects of a policy itself but also how the public institution responded to it. 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 contributes to the growing economic literature on child welfare by providing the first empirical evidence on how CPS foster care placement policies respond to 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 recessions (Brooks-Gunn, Schneider and Waldfogel, 2013), and climate change (Evans, Gazze and Schaller, 2023), are not rare. The findings of this paper underscore the importance of institutional adaptability in maintaining effective protection system during crises. In particular, funding mechanisms that adjust with caseloads and facilitate timely resource deployment can help agencies sustain their protective capacity when maltreatment risk rises.

The remainder of this paper proceeds as follows. Section 2 provides background information that helps interpret the empirical results. Section 3 describes the data and presents descriptive statistics. Section 4 outlines the empirical strategy. Section 5 presents the main empirical results. Section 6 explores potential mechanisms for the main empirical results. Section 7 concludes.

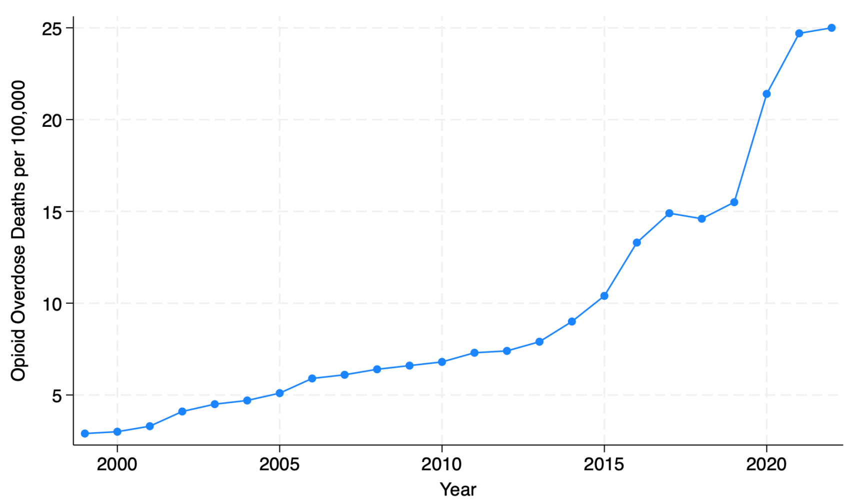
2 Background

This section provides background information to contextualize the results presented in section 5. Section 2.A provides documented facts about the opioid epidemic. Section 2.B discusses how the reformulation of OxyContin worsened the opioid epidemic. Section 2.C reviews empirical findings on the association between parental substance abuse and child maltreatment. Section 2.D offers an overview of the Child Protective Services (CPS) in the U.S.

2.A Opioid Epidemic

From 1999 to 2022, nearly 727,000 people died from an opioid overdose in the U.S. (CDC, 2023). The opioid overdose death rate increased significantly from 2.9 per 100,000 people in 1999 to 25.0 per 100,000 in 2022 (NCHS, 2023). The unprecedented rise 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).

Figure 1: Opioid Overdose Deaths



Notes. Opioid overdose deaths per 100,000 population from the National Vital Statistics System (NVSS).

Starting in the 1990s, changing perceptions of opioids and updated treatment protocols led physicians to prescribe opioids more frequently and at higher doses to manage pain (Jones et al., 2018). The American Pain Society initiated a significant campaign to recognize pain as the fifth vital sign in 1995, meaning that clinicians were encouraged to assess and document patients' pain levels as routinely as they measured temperature, pulse, respiration, and blood pressure. 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, which reinforced the expectation that pain should be treated aggressively, often with opioids (Phillips, 2000).

After its introduction by Purdue Pharma in 1996, OxyContin (oxycodone hydrochloride), an opioid painkiller, rapidly emerged as one of the top substances misused in the U.S. with global sales reaching $35 billion (Cicero, Inciardi and Muñoz, 2005). OxyContin releases its opioids slowly over 12 hours, meaning that it contained much higher dosage of opioids compared to other prescription opioid painkillers at the time. 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. However, individuals could unlock the high dosage of opioids 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, suggesting it as a primary cause of the opioid epidemic (Alpert et al., 2022; Arteaga and Barone, 2022).

2.B Reformulation of OxyContin

In response to the escalating misuse of OxyContin, Purdue Pharma released an abuse-deterrent formulation of the drug, which was approved by the Food and Drug Administration (FDA) in 2010. The reformulated OxyContin was designed to be more difficult to dissolve or crush, making it more challenging to abuse through ingestion, inhalation, or injection for immediate euphoric effects. Following the reformulation, OxyContin misuse rate declined as intended. 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 (opioid ingredient of OxyContin) declined after the reformulation, ending a consistent rise that had been ongoing since 2000 (Alpert, Powell and Pacula, 2018).

However, studies have documented a series of unintended consequences of the reformulation. The reformulation led to an increase in the overall opioid overdoses (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019), which was primarily driven by the use of and deaths related to heroin and synthetic opioids such as fentanyl (Alpert, Powell and Pacula, 2018; Evans, Lieber and Power, 2019). These results indicate that a considerable share of OxyContin users shifted to substitute drugs that were both illegal and more addictive, leading to a substantial growth of the illicit drug market. In addition, the reformulation led to a higher incidence of blood-borne diseases such as Hepatitis and HIV due to injection drug use (Beheshti, 2019), and even rising violent crime, as reflected in higher homicide rates (Park, 2022; Tan, 2024).

2.C 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).

These results suggest that the reformulation of OxyContin increased children's exposure to maltreatment risk at home through multiple channels. First, an increase in drug overdoses indicates that more parents presumably overdosed as well, which would have increased child maltreatment risk. 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 impairs parenting abilities of users, increasing children's exposure to maltreatment risk. Third, crimes associated with obtaining heroin may have further increased risk to children. Unlike prescription opioids, heroin and the majority of synthetic opioids are classified as Schedule I substances under the Controlled Substances Act, making them illegal to purchase and often driving high-risk criminal behaviors to obtain them.

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 a growth of the illicit drug market 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.

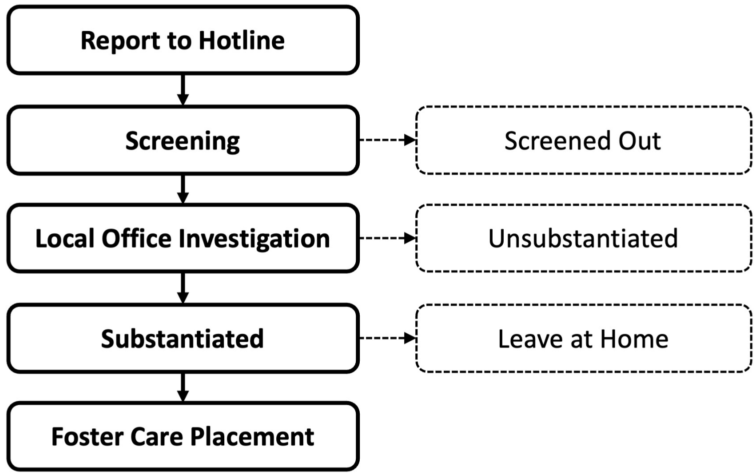
2.D Child Protective Services (CPS) in the United States

More than one-third of children in the U.S. experience a child welfare investigation (Kim et al., 2017). By the age of 18, approximately 6% of all children, including 15% of Native American children and 10% of Black children, will have entered foster care at some point in their lives (Wildeman and Emanuel, 2014). Figure 2 demonstrates the child maltreatment investigation process in the United States. When child maltreatment is suspected, any individual can make a report by calling a hotline. Certain professionals, such as teachers and physicians, are legally mandated reporters. These reports are then screened to determine if they warrant further investigation, with screened-in cases being routed to local CPS offices. Screening decisions depend on two criteria: whether there is enough identifying information to initiate the investigation and whether the allegation meets the statutory definitions of child maltreatment. Approximately 60 to 70 percent of reports are screened in and advance to the investigation stage as formal allegations. Once the allegations reach 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.[1] This means that CPS is mandated to predict whether a child would be maltreated if left at home rather than placed in foster care. When investigators conclude that remaining at home poses such a risk, they file a court petition seeking removal and foster care placement. Once placed, children reside in foster care while efforts are made to address the underlying issues within their families. Parents are typically required to comply with a reunification plan, which may involve participation in rehabilitation or detox programs, especially when parental substance abuse is the cause of the child's removal. The ultimate goal of CPS is to reunify families whenever it is safe and feasible, though this process often involves navigating complex and

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

Figure 2: Overview of Child Maltreatment Investigations



Notes. This figure demonstrates the process for child maltreatment investigations in the United States. "Substantiated" indicates that Child Protective Services (CPS) found sufficient evidence to support maltreatment allegations. Conditional on substantiation, CPS may place children in foster care if it is suspected that they would face maltreatment if left at home.

challenging tensions between child welfare, parental rights, and the best interests of the child.

3 Data

This section describes the data used in the empirical analyses. Section 3.A introduces the child welfare data used in the main analyses. Section 3.B presents the opioid data used to construct the exposure measures. Section 3.C outlines the child welfare expenditure data. Section 3.D reports descriptive statistics.

3.A Child Welfare Data

3.A.1 Overview

The primary data for child welfare are collected from the National Child Abuse and Neglect Data System (NCANDS) and the Adoption and Foster Care Analysis and Reporting System (AFCARS). NCANDS is a federally funded initiative that gathers yearly data on child abuse and neglect cases reported to CPS across the United States. Reporting to NCANDS by states is voluntary, yet the majority of states and the District of Columbia provide data during the timeframe of the analysis in this paper.[2] AFCARS, a data collection system required by federal mandate, gathers detailed information on all children protected under Title IV-B/E of the Social Security Act (Section 427). This database compiles data on every child in foster care and those adopted through the jurisdiction of state child welfare agencies. Since 1998, it has been compulsory for states to participate in this program. I use NCANDS Child Files 2004-2018 and AFCARS Foster Care Files 2004-2018 for the analysis.[3] For the analysis of foster care placements, I exclude six states that did not report placement outcomes in the NCANDS files.[4]

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 percent of the U.S. population. Second, I create "super counties" in each state by aggregating outcome and control variables across all counties with fewer 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.

I focus on allegations reported by professionals. These report sources include social services, medical, mental health, legal, education personnel, and child daycare providers. As shown in Table A3, 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.

First, 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.

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

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

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

Second, professionals are less likely to be drug abusers themselves. While the reformulation of OxyContin could have compromised the reporting behavior of some individuals, professionals are comparatively insulated. 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).

3.A.2 Measures of False Negatives

NCANDS data contain Child IDs that allow matching across allegations. This feature makes it possible to track subsequent outcomes of initial investigations in which children were left at home. This information can be used for assessing whether children who remained at home were in fact at risk of subsequent maltreatment. Manuals for CPS investigators clearly state that foster care placement should occur when there is a potential risk of maltreatment if a child is left at home. Investigators should therefore assess the risk of subsequent maltreatment and predict the likelihood of harm. False negatives occur when CPS mistakenly leaves an at-risk child at home. Formally, let $Y_i^* \in \{0, 1\}$ denote the maltreatment potential, equal to 1 if a child i would be maltreated if left at home. Let $D_i \in \{0, 1\}$ denote the placement decision for i, equal to 1 if child i is placed in foster care. I define a false negative as

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

The empirical challenge in measuring false negatives lies in the fact that Y_i^* is a latent variable. Reinvestigations within six months of the initial investigation where the child was left at home are widely used as a proxy for subsequent maltreatment in the academic research and serve as a quality metric among policymakers (Antle et al., 2009; Putnam-Hornstein et al., 2015; Putnam-Hornstein, Prindle and Hammond, 2021; Baron et al., 2024*a*,*b*). Reinvestigations involve considerable interactions with authorities that entail a report to CPS and screening procedures in the central hotline center. In section 5.C, I show the robustness of the main results to alternative measures of false negatives that involve decisions of CPS, including subsequent substantiation and foster care placement.

For the analysis of false negatives, I exclude states where the successful matching rate between Child Files from t to $t + 1$ is below 90% for more than two years within the period $t \in$

$\{2004, \cdots, 2015\}$.[5] Additionally, I exclude states that do not report foster care placements. These criteria yield a sample of 39 states and 417 counties (including super counties) for the analysis of false negatives.

3.B OxyContin and Prescription Opioid Data

The identification strategy in this paper compares outcomes across regions that were more versus less exposed to the reformulation. I construct exposure measures based on the patterns of opioid use in each region. The intuition for the construction of exposures is that the reformulation had more "bite" on regions where more people were dependent on high-risk prescription opioids including OxyContin.

For the state-level analysis, I utilize the measures for OxyContin misuse, 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 OxyContin misuse rate 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).

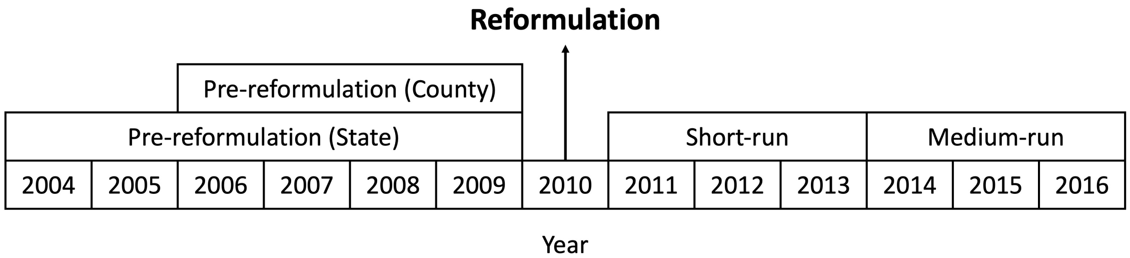
Since the OxyContin misuse data is only available at the state level, I use Schedule II prescription opioid data from the Centers for Disease Control and Prevention (CDC), covering the period from 2006 to 2009 for the county-level analysis.[6] This data includes nearly 85% of all retail pharmacy providers in the United States, excluding hospitals. The pre-reformulation exposure 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.

Table 3 presents the sample timeline. State-level panel spans 2004 to 2016 and state-level exposures are constructed using the years 2004-2009. County-level panel spans 2006 to 2016

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

[6] 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 3: Sample Timeline



Notes. This figure presents the timeline of the sample. The reformulation of OxyContin occurred in 2010. Exposures are constructed using pre-reformulation data. State-level exposures are based on OxyContin misuse data from 2004 to 2009, while county-level exposures are based on Schedule II prescription opioid data from 2006 to 2009. The "short-run" refers to the three years immediately following the reformulation (2011–2013), while the "medium-run" refers to the subsequent three years (2014–2016).

as the Schedule II prescription opioids data are available beginning in 2006. County-level exposures are constructed using the years 2006-2009. For robustness, I also compute alternative exposures using only the first half of the pre-reformulation periods: 2004–2006 at the state level and 2006–2007 at the county level. These alternative measures are highly correlated with the primary ones as shown in Figure A2. For the empirical analysis, I partition the post-reformulation period into two blocks: the short run, referring to the three years immediately following the reformulation (2011–2013), and the medium run, referring to the subsequent three years (2014–2016).

3.C Child Welfare Expenditure Data

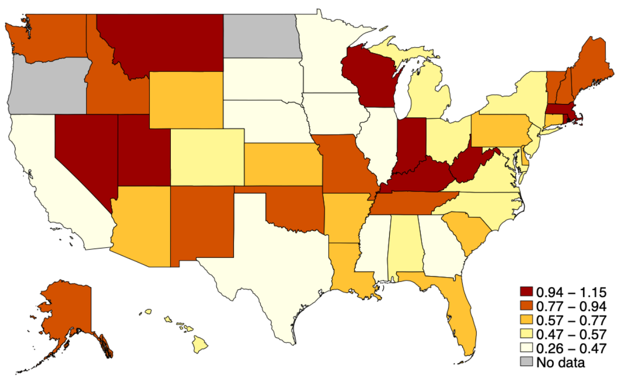
To analyze the fiscal response to the opioid epidemic, I use biannual, state-level data from the Child Welfare Financing Surveys for the years 2006 to 2016. These surveys were conducted by Child Trends, with financial data collected from all 50 states and the District of Columbia.

The surveys document state-reported child welfare expenditures across multiple funding sources, including federal, state, and local funds. Expenditures encompass a wide array of activities such as child protection services, case management, foster care, adoption services, administrative overhead, and staff salaries, as well as services for prevention and family preservation. The federal funds are drawn from both dedicated child welfare programs such as Titles IV-B and IV-E of the Social Security Act and non-dedicated programs including Medicaid, the Social Services Block Grant (SSBG), and Temporary Assistance for Needy Families (TANF).

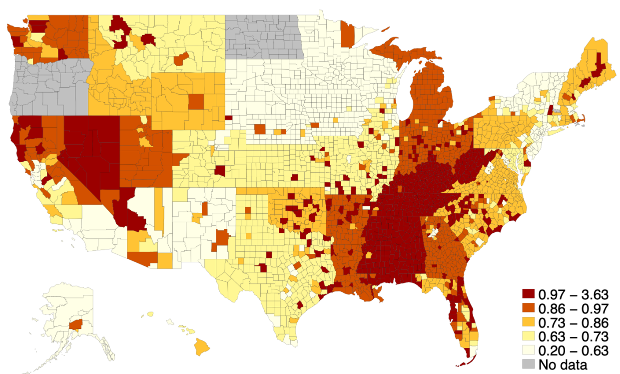
Data collection was administered via mailed surveys to each state's child welfare administrator, as listed by the National Association of Public Child Welfare Administrators (NAPCWA). To ensure data quality, states were contacted for follow-up if reported spending in any category changed by more than 20 percent compared to the previous wave. After reconciliation, a one-page summary of reported expenditures was sent to each state for final review and confirmation. States were asked to verify their data or flag any necessary revisions, improving the reliability and consistency of reported figures across survey waves.

3.D Descriptive Statistics

Figure 4: Geographic Distribution of Exposures by State and County



(a) State

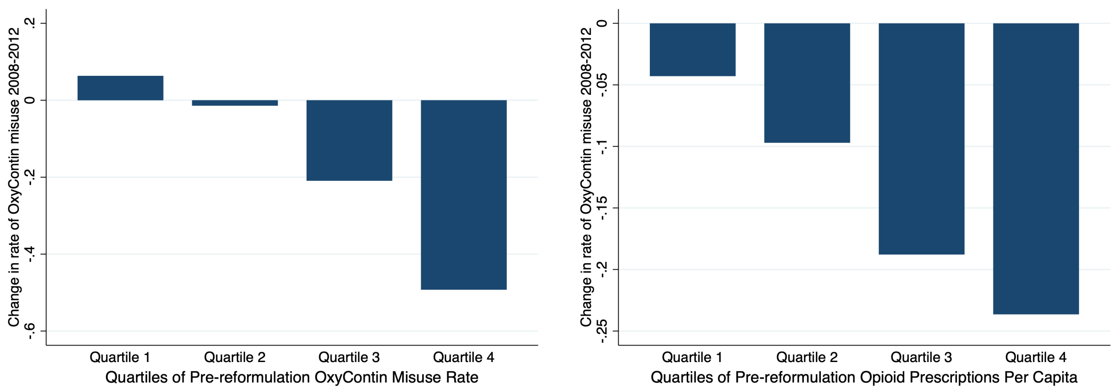


(b) County

Notes. This figure illustrates the measures of exposure to the reformulation of OxyContin by state and counties. Figure (a) shows OxyContin misuse rates between 2004 and 2009 across states. Figure (b) shows Schedule II opioid prescriptions per capita across 597 identified counties and 46 super counties between 2006 and 2009, where counties with less than 700 allegations in each state are classified as super counties due to masked county IDs.

Figure 4 shows the geographic distribution of the pre-reformulation OxyContin misuse rate by state and Schedule II prescription opioids per capita by county. The exposures for super counties in Figure (b) are 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 exposures at both the state and county levels. Figure A1 demonstrates the correlation between standardized state- and county-level exposures. To assess the correlation between these two measures, I aggregated the county-level measure to the state level using county population weights. The two measures are highly correlated: a one standard deviation increase in the county-level measure is associated with a 0.55 standard deviation increase in the state-level measure.

Figure 5: Relevance of Exposures



(a) State

(b) County

Notes. This figure presents the change in the OxyContin misuse rates between 2008 and 2012 across quartiles of the exposures 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).

Figure 5 shows that the reformulation of OxyContin had a stronger impact in regions with higher exposure. 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 and counties with higher exposures 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

Table 1: Summary Statistics

	Pre-reformulation			Post-reformulation		
	Low-exposure	High-exposure	p-value	Low-exposure	High-exposure	p-value
Panel A: States						
Allegations	219.93	297.11	0.108	245.08	356.88	0.014
False Negatives	13.25	16.33	0.150	16.32	26.78	0.006
Percent Black	14.53	9.58	0.054	14.72	10.06	0.079
Percent Female	50.88	50.83	0.803	50.83	50.76	0.727
Percent Child	27.90	26.72	0.094	26.50	25.34	0.174
Unemployment Rate	6.01	5.44	0.062	7.31	6.90	0.337
Labor Force Participation Rate	66.08	65.60	0.640	63.63	62.96	0.499
Panel B: Counties						
Allegations	228.65	286.29	0.054	241.90	354.01	0.002
False Negatives	14.40	15.43	0.596	17.96	24.15	0.058
Percent Black	12.50	14.36	0.307	12.76	14.60	0.307
Percent Female	50.80	50.95	0.310	50.75	50.91	0.227
Percent Child	13.11	12.87	0.299	13.05	12.81	0.347
Unemployment Rate	5.89	6.64	0.029	7.08	7.58	0.134
Labor Force Participation Rate	64.10	61.12	0.000	62.39	58.50	0.000

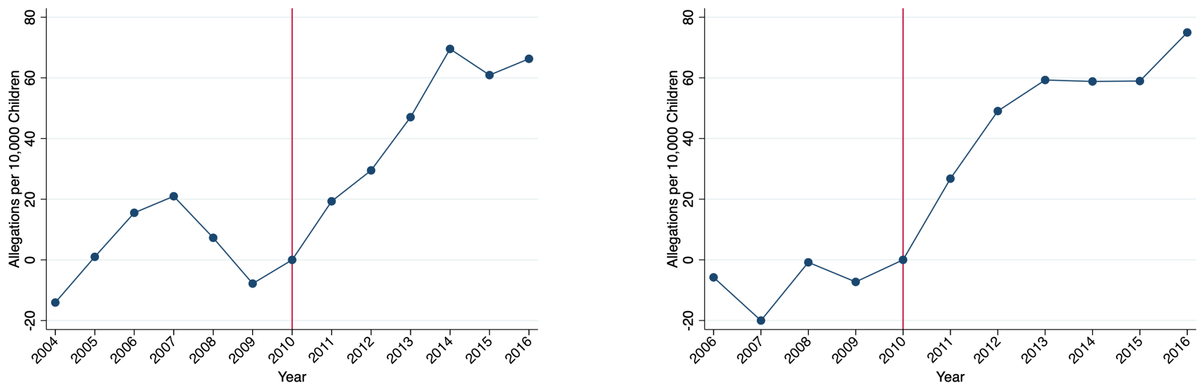
Notes. This table presents summary statistics for low- and high-exposure states and counties, separately for the pre-reformulation period (2004–2009 for states and 2006-2009 for counties) and the post-reformulation period (2010–2016). High-exposure states are those with an above-median pre-reformulation OxyContin misuse rate, while high-exposure counties are those with an above-median pre-reformulation Schedule II prescription opioids per capita. Allegations and false negatives are measured per 10,000 children. The third and sixth columns report p-values from tests for the equality of means.

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 main outcomes of interest are maltreatment allegations per 10,000 children, and false negatives measured both per 10,000 children and per 1,000 allegations. False negatives measured per 10,000 children and per 1,000 allegations each offer distinct and complementary insights. False negatives per 10,000 children reflect how many at-risk children in the population were missed by the system, providing a direct measure of the 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, since a false negative can occur only when an allegation exists, false negatives per 10,000 children conflate changes in reporting with changes in CPS responses. False negatives per 1,000 allegations isolate CPS decision-making conditional on the set of cases they observe, providing a more direct measure of how CPS handled allegations during the opioid epidemic.

Table 1 presents summary statistics for low- and high-exposure states and counties,

Figure 6: Differential Trends in Maltreatment Allegations



(a) Allegations by State

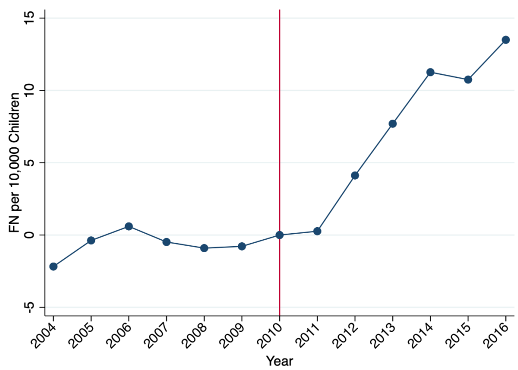
(b) Allegations by County

Notes. This figure illustrates the trends in the differences in maltreatment allegations per 10,000 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. Differences in 2010 are normalized to 0.

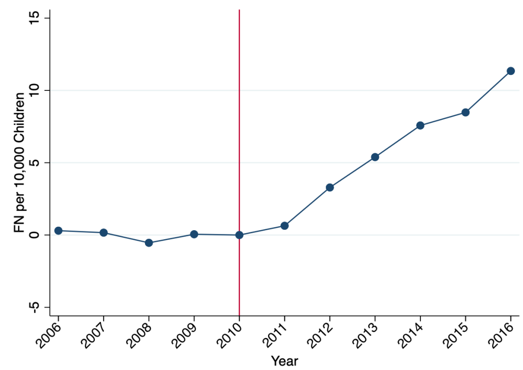
separately for the pre-reformulation period (2004–2009 for states and 2006-2009 for counties) and the post-reformulation period (2010–2016). High-exposure states are those with an above-median pre-reformulation OxyContin misuse rate, while high-exposure counties are those with an above-median pre-reformulation Schedule II prescription opioids per capita. The third column reports p-values from tests for the equality of means. Prior to the reformulation, high-exposure regions exhibited higher rates of allegations per 10,000 children, but the differences were not statistically significant. After the reformulation, the gap widened and became statistically significant. False negatives per 10,000 children follow a similar pattern: pre-reformulation differences were insignificant, but they became significant in the post-reformulation period as the gap expanded.

To descriptively assess how outcomes evolved before and after the reformulation in areas with different levels of exposure, I examine trends in outcome differences between high- and low-exposure states and counties, normalizing the differences in 2010 to 0. 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 6 presents differential trends in maltreatment allegations per 10,000 children. Compared to the pre-reformulation periods, the differences in maltreatment allegations increased substantially and almost monotonically following the reformulation, suggesting that regions more heavily affected by the opioid supply disruption experienced relatively larger increases in maltreatment allegations.

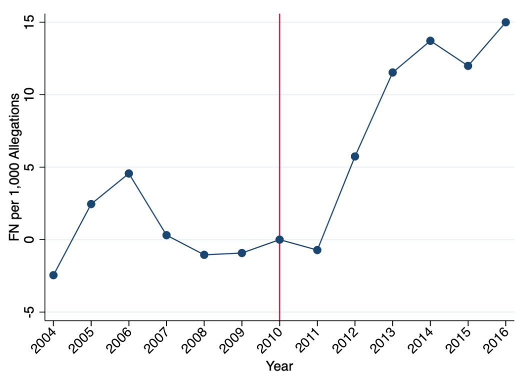
Figure 7: Differential Trends in False Negatives



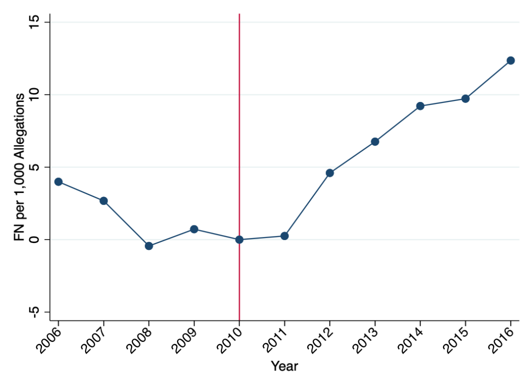
(a) FN by State, per 10,000 Children



(b) FN by County, per 10,000 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 10,000 children and per 1,000 allegations between high- and low-exposure states and counties. False negatives refer to cases in which children were reinvestigated within six months after not being placed in foster care following the initial investigation. 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. Differences in 2010 are normalized to 0.

Figure 7 presents differential trends in false negatives per 10,000 children and 1,000 allegations. Prior to the reformulation, the differences in false negatives per 10,000 children were close to zero. 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. Similar trends are observed for false negatives per 1,000 allegations, which indicate that a larger share of allegations resulted in missed maltreatment cases in high-exposure regions compared to low-exposure regions.

These descriptive trends reveal that the reformulation led to widening disparities between high- and low-exposure regions in both the volume of allegations and at-risk children missed by CPS. High-exposure states and counties experienced relatively larger increases in maltreatment allegations, yet CPS responses did not scale to the heightened risk of maltreatment, leaving more children unprotected. In the next section, I turn to an event study and difference-in-differences framework to formally quantify the causal effect of the reformulation on child maltreatment and CPS responses by leveraging geographic variation in the exposure to the reformulation.

4 Empirical Strategy

The empirical strategy is based on the exposure design, which is akin to Bartik or shift-share approaches. In this setting, the nationwide reformulation of OxyContin in 2010 serves as a common policy shock, while pre-reformulation OxyContin misuse rates (at the state level) or Schedule II opioid prescription rates (at the county level) serve as pre-determined measures of exposure. Unlike the canonical Bartik design, the interaction of the exposure measure and the common shock is not used as an instrument for an endogenous treatment variable. Instead, the focus is on estimating the intent-to-treat (ITT) effect of the reformulation across areas with different levels of pre-reformulation exposure. Similar ITT approaches have been employed in prior studies of the OxyContin reformulation (Beheshti, 2019; Powell and Pacula, 2021; Evans, Harris and Kessler, 2022; Park, 2022).

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:

$$y_{st} = \sum_{\substack{k=2004 \\ k\neq 2010}}^{2016} \beta_k \mathbb{1}[t=k] \times \text{Exp}_s + \alpha_s + \gamma_t + X'_{st}\lambda + \epsilon_{st} \tag{2}$$

$$y_{ct} = \sum_{\substack{k=2006 \\ k\neq 2010}}^{2016} \gamma_k \mathbb{1}[t=k] \times \text{Exp}_c + \alpha_c + \gamma_t + X'_{ct}\lambda + u_{ct} \tag{3}$$

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) OxyContin misuse rate and Exp_c denotes a standardized pre-reformulation (2006-2010) Schedule II opioid prescriptions per capita in county c. X_{st} denotes a vector of state- and time-varying covariates including the percentage of Black, female, and child population, 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. Regressions are estimated using weighted least squares, weighting by the child population in each state and year. 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 the reformulation. I estimate the following equations:

$$\begin{aligned} y_{st} = {} & \beta_1 \times \text{Pre}_t^S \times \text{Exp}_s + \beta_2 \times \text{SRpost}_t \times \text{Exp}_s + \beta_3 \times \text{MRpost}_t \times \text{Exp}_s \qquad (4) \\ & + \alpha_s + \gamma_t + X_{st}'\lambda + \epsilon_{st} \\ y_{ct} = {} & \gamma_1 \times \text{Pre}_t^C \times \text{Exp}_c + \gamma_2 \times \text{SRpost}_t \times \text{Exp}_c + \gamma_3 \times \text{MRpost}_t \times \text{Exp}_c \qquad (5) \\ & + \alpha_c + \gamma_t + X_{ct}'\lambda + u_{ct} \end{aligned}$$

where Pre_t^S and Pre_t^C equal 1 for years 2004–2009 and 2006–2009, respectively. SRpost_t equals 1 for years 2011–2013, and MRpost_t equals 1 for years 2014–2016. Standard errors are clustered at the state level. Regressions are estimated using weighted least squares, weighting by the child population in each county and year. 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 the magnitudes of these effects grow 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 "dose" of the reformulation and (2) are not correlated with factors that could affect the differential trends in the outcomes following the reformulation, in the absence of the reformulation. The first assumption is supported by the results in Figure 5, which shows that regions with higher exposure experienced larger declines in the OxyContin misuse rate following the reformulation, providing empirical evidence for the relevance of the exposures.

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 pretrend 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. I also test the balance of covariates by showing that the exposure measure is orthogonal to pre-reformulation changes in X_{st} and X_{ct}. These results are reported in Table A2.

5 Results

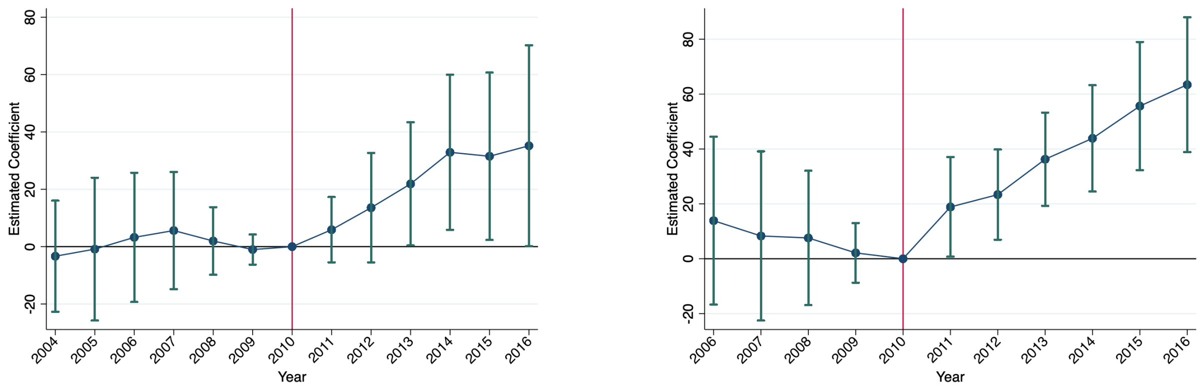
In this section, I present the empirical results. Section 5.A presents the main results for maltreatment allegations and false negatives. Section 5.B examines heterogeneous effects by characteristics of children and allegations. Section 5.C assesses the robustness of the main findings.

5.A Main Results

5.A.1 Maltreatment Allegations

Figure 8 and Table 2 present the event study and difference-in-differences results for allegations per 10,000 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 an increase of about 14 additional allegations per 10,000 children in the short run and 33 additional allegations in the medium run. These changes correspond to 5.7 percent and 13.7 percent increases relative to the baseline mean, respectively, amounting to approximately 333,000 and 798,000 additional allegations nationwide. At the county level, a one standard deviation increase in pre-reformulation Schedule II opioid prescriptions per capita yields an increase of about 26 additional allegations per 10,000 children in the short

Figure 8: Event Study Results for Allegations per 10,000 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 2 and Equation 3 that are adjusted for within-state clustering. The dependent variable is maltreatment allegations per 10,000 children. Figure (a) is based on a state-level analysis, whereas Figure (b) is based on a county-level analysis. Regressions are weighted by child population.

run and 54 additional allegations in the medium run, corresponding to 10.9 percent and 22.5 percent increases relative to the baseline mean. In aggregate terms, these effects amount to roughly 637,000 and 1.3 million additional allegations.

To put these magnitudes in perspective, the estimated medium-run increases are sizable when compared to pre-existing racial disparities in allegations. Prior to the reformulation, the rate of maltreatment allegations was 387 per 10,000 Black children and 181 per 10,000 White children, a gap of 206 allegations. The medium-run effects of the reformulation of OxyContin therefore amount to roughly one-sixth to one-quarter of this Black–White gap, highlighting that the increases in allegations were not only statistically significant but also large in substantive terms.

An increase in the allegations indicates that the underlying maltreatment risk increased following the reformulation of OxyContin. This heightened risk is presumably driven by the exacerbation of the opioid epidemic after the reformulation. As documented in the existing literature, the reformulation led to increases in opioid overdose deaths, use of heroin and synthetic opioids, cases of hepatitis and HIV, homicides, and heroin-related arrests. Given the strong link between parental substance use and child maltreatment, these findings reflect the elevated risk faced by vulnerable children during periods of rising opioid misuse. Moreover, the larger effects observed in the medium run are consistent with the existing

Table 2: Difference-in-Differences Results for Allegations per 10,000 Children

	(1) Allegations State	(2) Allegations County
Pre-reformulation	1.00	7.90
	(7.63)	(11.69)
Short-run	13.66*	26.12***
	(7.86)	(8.11)
	[5.7%]	[10.9%]
Medium-run	32.88**	54.06***
	(14.86)	(10.68)
	[13.7%]	[22.5%]
Mean	239.76	239.76
R-Squared	0.869	0.867
Observations	634	7073
State or County FE	Yes	Yes
Year FE	Yes	Yes
X_{st} or X_{ct}	Yes	Yes

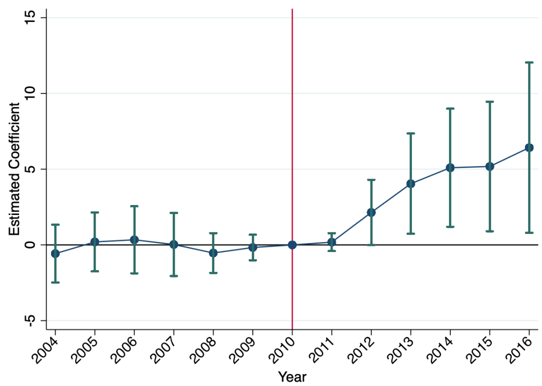
Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where the dependent variable is maltreatment allegations per 10,000 children. Column (1) is based on a state-level analysis whereas Column (2) is based on a county-level analysis. Regressions are weighted by 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

literature showing that the consequences of the reformulation were amplified over time, as substitution into heroin and synthetic opioids as well as maturation of the illicit market took time to manifest.

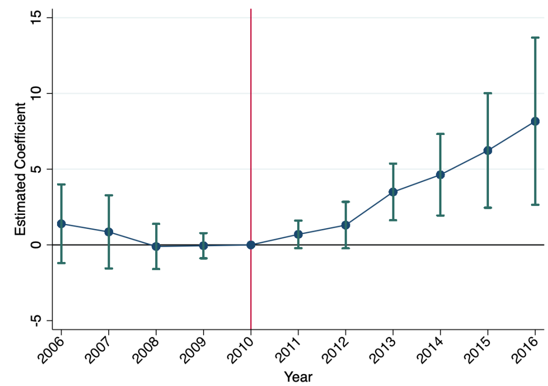
5.A.2 False Negatives

Figure 9 and Table 3 present the results for false negatives. Figures 9a and 9b, along with Columns (1) and (2) of Table 3, report the estimates for false negatives per 10,000 children. At the state level, a one standard deviation increase in the pre-reformulation OxyContin misuse rate corresponds to about 2 additional false negatives per 10,000 children in the short run and 5 additional false negatives in the medium run. These increases represent 13.9 percent and 36.5 percent growth relative to the baseline mean, respectively. At the county level, a one standard deviation increase in pre-reformulation Schedule II prescription opioids per capita yields about 2 additional false negatives per 10,000 children in the short run and 6 additional false negatives in the medium run, corresponding to 12.3 percent and 42.4 percent increases relative to the baseline. In aggregate terms, these estimates imply that roughly 45,000–50,000 at-risk children in the short run and 130,000–150,000 in the medium run were left at home without protection.

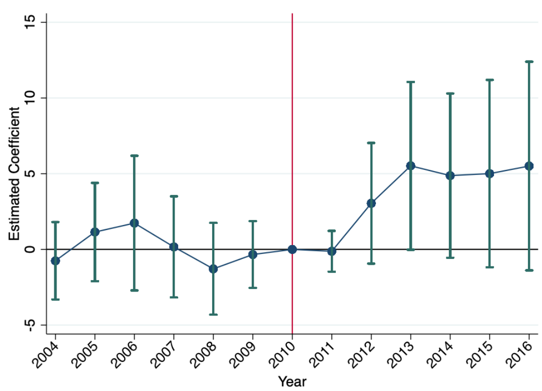
Figure 9: Event Study Results for False Negatives



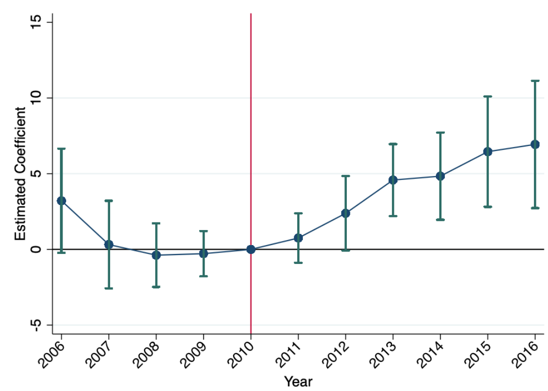
(a) FN by State, per 10,000 Children



(b) FN by County, per 10,000 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 2 and Equation 3 that are adjusted for within-state clustering. The dependent variables are false negative rates. False negatives refer to cases in which children were reinvestigated within six months after not being placed in foster care following the initial investigation. Figures (a) and (b) report the results for false negatives per 10,000 children whereas Figures (c) and (d) report the results for false negatives per 1,000 allegations. Figures (a) and (c) are based on a state-level analysis whereas Figures (b) and (d) are based on a county-level analysis. Regressions are weighted by child population.

In addition, false negatives rose when measured relative to the volume of allegations. Figures 9c and 9d, along with Columns (3) and (4) of Table 3, report the estimates for false negatives per 1,000 allegations. At the state level, a one standard deviation increase in the pre-reformulation OxyContin misuse rate corresponds to roughly 3 additional false negatives per 1,000 allegations in the short run and about 5 additional cases in the medium run, although the estimates are statistically significant only at the 10 percent significance level. These estimates translate into 4.5 percent and 8.1 percent increases from the relative to the baseline mean. At the county level, the same increase in pre-reformulation opioid prescriptions per capita translates into about 3 additional false negatives per 1,000 allegations in the short run and 6 additional cases in the medium run, corresponding to 4.1 percent and 9.7 percent increases relative to the baseline mean, respectively. A rise in the false negatives per 1,000 allegations indicate that a growing share of allegations resulted in missed maltreatment cases following the reformulation.

5.B Heterogeneity Analysis

Table A3 presents the percentage breakdown of allegations by maltreatment type, child characteristics, and report sources, separately for all allegations and for those made by professionals during the sample period from 2004 to 2016. Neglect is the most common type of maltreatment, comprising 60.4% of all allegations, followed by physical abuse, which accounts for 21.8%. Among professional reports, neglect and physical abuse remain the most frequent types of maltreatment, making up approximately 77% of these allegations. Education, legal, social services, and medical personnel are the most common sources of reports, accounting for 51% of all allegations. Among reports made by professionals, these groups represent 91% of the total.

Figures A7, A8 and Tables A6, A7 present the results for allegations by maltreatment type and child characteristics. These findings show that both physical abuse and neglect increased following the reformulation. With respect to child characteristics, the rise in allegations was not concentrated in specific subgroups but was observed across all groups.

Figures A3, A4, A5, and A6, along with Tables A4 and A5, 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. The rise in allegations was not disproportionately concentrated in any single occupation. Instead, allegations increased across multiple professional groups, suggesting that the pattern was not driven by an occupation-specific effect.

Table 3: Difference-in-Differences Results for False Negatives

	(1) FN Children State	(2) FN Children County	(3) FN Allegations State	(4) FN Allegations County
Pre-reformulation	-0.14	0.49	0.03	0.65
	(0.75)	(0.81)	(1.31)	(1.44)
Short-run	2.06**	1.82***	2.78*	2.54**
	(0.91)	(0.55)	(1.63)	(1.13)
	[13.9%]	[12.3%]	[4.5%]	[4.1%]
Medium-run	5.40**	6.27***	5.00*	6.01**
	(2.19)	(1.96)	(2.93)	(2.76)
	[36.5%]	[42.4%]	[8.1%]	[9.7%]
Mean	14.78	14.78	61.84	61.84
R-Squared	0.74	0.71	0.77	0.70
Observations	506	4587	506	4587
State or County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where the dependent variables are false negatives rates. Columns (1) and (2) report the results for false negatives per 10,000 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figures A9, A10, A10, A12, A14 and A13, along with Tables A9, A8, A11, and A10 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.

5.C Robustness Checks

Figures A16, A15 and Tables A13, A12 present the event study and difference-in-differences results for alternative measures of false negatives. These measures are based on subsequent CPS decisions, including substantiation and foster care placements within six months of an initial investigation that resulted in the child being left at home. The reason for relying on subsequent reinvestigation as the primary measure of false negatives is that when a child is re-reported within a few months, the initial investigator is often reassigned to the case. As a result, such outcomes may capture investigator-specific placement tendencies, rather than the underlying risk. In contrast, subsequent reinvestigation is independent of the initial investigator. Figures A18, A17 and Tables A15, A14 present the results based on the alternative time frames between the focal and subsequent investigation for defining false negatives. The results are robust to subsequent allegations within 3 months, 9 months, and 12 months following the initial investigation.

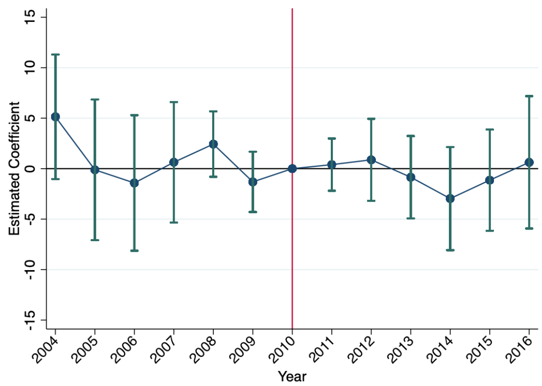
Alternative empirical specifications have been estimated for robustness checks. Figure A19 and Table A17 present results based on a binary treatment, where the exposure measure is defined as an indicator taking the value of one if the state's pre-reformulation OxyContin misuse rate is above the median and if the county's pre-reformulation Schedule II prescription opioids per capita are above the median. Table A16 shows the regression results where the exposure measure is binned into quartiles, with the first quartile serving as the reference group. Figures A21, A22 and Table A19 present the results based on alternative exposure measures. State-level exposures are computed as the OxyContin misuse rate from 2004 to 2006. County-level exposures are computed as the Schedule II prescription opioids per capita from 2006 to 2007. Figure A20 and Table A18 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. Finally, Figures A23, A24 and Tables A20, A21 present the results excluding the economic covariates and policy variables from the set of covariates, as some of these covariates may be affected by the reformulation. These results confirm that the main findings are robust to these alternative specifications.

6 Mechanisms

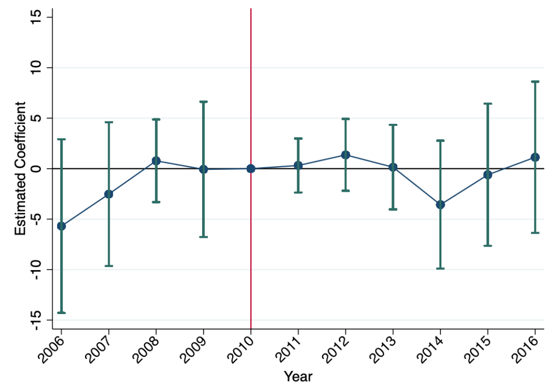
This section explores potential mechanisms behind the rise in false negatives following the reformulation. In particular, it focuses on mechanisms driving the increase in false negatives conditional on allegations as presented in Figures 9c and 9d, along with Columns (3) and (4) of Table 3. Section 6.A presents results on foster care placements, which reflects the extent to which CPS scaled protective actions in response to the epidemic. Section 6.B reports results on child welfare agency expenditures, capturing the fiscal response. Section 6.C provides suggestive evidence on the role of the supply of foster homes, which may have constrained CPS responses during the epidemic. All outcome variables in this section are measured per allegation, as the focus is on CPS responses conditional on the cases they observed. The same subsample for the analysis of false negatives has been used throughout this section.

6.A Foster Care Placements

Figure 10: Event Study Results for Placements 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 2 and Equation 3 that are adjusted for within-state clustering. The dependent variables are foster care placements per 1,000 allegations. Figure (a) is based on a state-level analysis, whereas Figure (b) is based on a county-level analysis. Regressions are weighted by child population.

Figure 10 and Table 4 present the event study and difference-in-differences results for foster care placements per 1,000 allegations. Thes results show that changes in foster care placements per 1,000 allegations were statistically indistinguishable from zero. This pattern indicates that CPS continued to place the same share of allegations in foster care before and after the reformulation. However, the simultaneous increase in false negatives per 1,000 allegations alongside flat placement rates suggests that CPS did not adjust its placement policies in response to the rising share of at-risk children, resulting in a greater share of missed maltreatment cases.

6.B Child Welfare Expenditures

The ability and capacity of CPS to respond effectively are closely tied to the financial resources devoted to child protection. Child welfare agencies operate with limited resources. Since they are mandated to investigate every allegation that enters the system, the volume of allegations directly drives demand for resources. Each investigation requires substantial

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

	(1) State Placement	(2) County Placement
Pre-reformulation	0.814	-1.776
	(1.899)	(2.504)
Short-run	0.167	0.579
	(1.608)	(1.474)
	[0.3%]	[0.9%]
Medium-run	-1.078	-1.099
	(2.405)	(3.368)
	[-1.6%]	[-1.7%]
Mean	66.18	66.18
R-Squared	0.767	0.755
Observations	506	4587
State or County FE	Yes	Yes
Year FE	Yes	Yes
X_{st} or X_{ct}	Yes	Yes

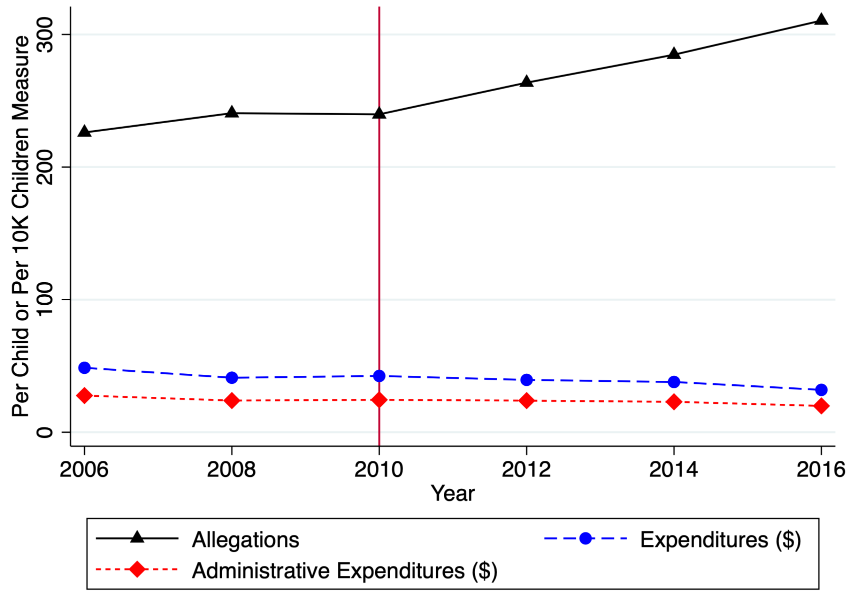
Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where the dependent variables are foster care placements per 1,000 allegations. Column (1) is based on a state-level analysis whereas Column (2) is based on a county-level analysis. Regressions are weighted 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

inputs, including caseworker time, administrative support, and when necessary, foster care or service provision. Consequently, expenditures per allegation provide a natural measure of whether child protection resources have kept pace with shifting demand.

Child welfare agencies are funded through a combination of federal, state, and local sources. Federal funding primarily comes from Titles IV-E and IV-B of the Social Security Act, which support core child welfare activities. In addition to federal funding, states contribute their own resources to operate federally mandated programs and to cover expenses not reimbursed by the federal government. Since 2008, state and local governments have accounted for approximately 55 to 57 percent of total child welfare expenditures, with the remaining share covered by federal sources.

Among the funding streams, the most relevant one for CPS investigation is the Foster Care Program of Title IV-E, which account for 11 percent of the total child welfare

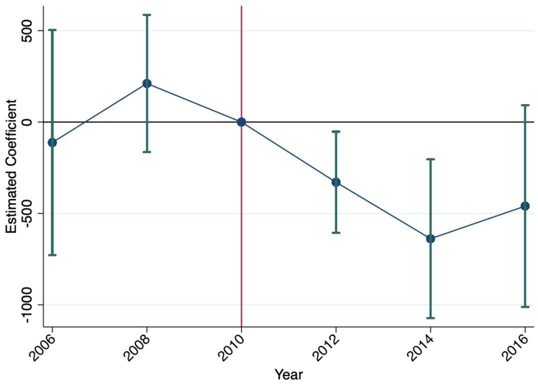
Figure 11: Trends in Allegations and Foster Care Expenditures



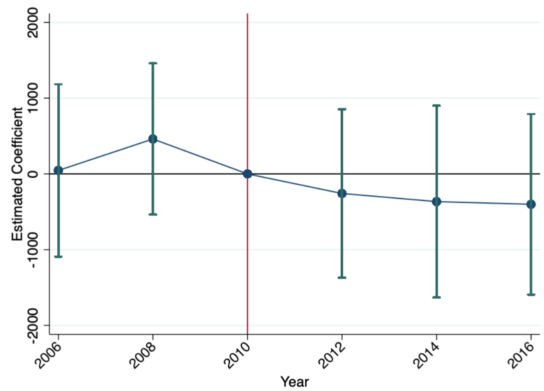
Notes. This figure presents trends in maltreatment allegations per 10,000 children, total foster care program expenditures per child, and foster care administrative expenditures per child. Total foster care program expenditures include any costs related to CPS investigation and foster care programs, including administrative and training expenses as well as foster care maintenance costs. Administrative expenditures specifically cover caseworker salaries, staff training, case planning and pre-placement activities, and information technology systems that support agencies in tracking and managing cases.

expenditures. These funds cover any costs related to CPS investigation and foster care programs, including administrative and training expenses as well as foster care maintenance costs. Between 50 to 75 percent of the expenditures for these activities are reimbursed by the federal government. Foster care administrative expenditures make up more than half of the total foster care expenditures, accounting for about 7 percent of the total child welfare agency expenditures. These include expenditures for caseworker salaries, staff training, case planning and pre-placement activities, and information technology systems for investigation. Because administrative expenditures are directly linked to the investigation of maltreatment allegations, they play a central role in determining the intensity and quality of CPS responses. In periods of heightened demand, such as during the opioid epidemic, the degree to which agencies could draw on these funding streams and supplement it with state and local resources critically shape their ability to expand investigative capacity and provide foster care services when necessary.

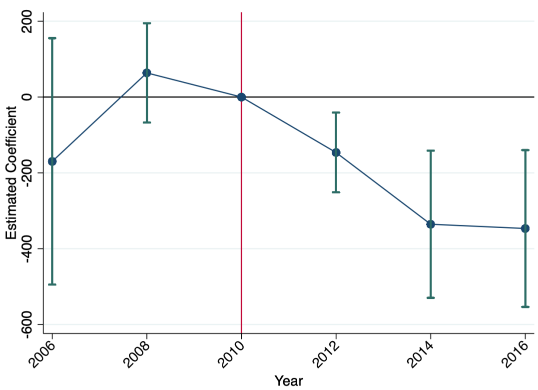
Figure 12: Event Study Results for Child Welfare Expenditures



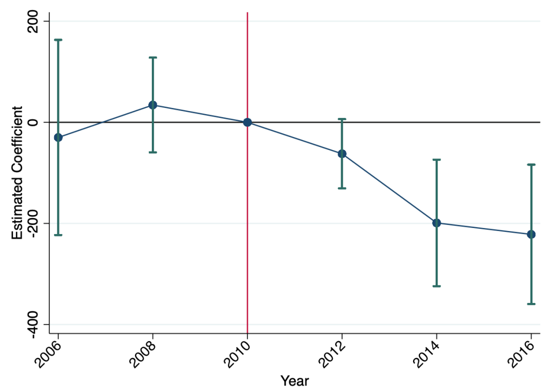
(a) Federal



(b) State



(c) Total Foster Care Program



(d) Foster Care Administrative

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 that is adjusted for within-state clustering. The dependent variables are child welfare expenditures per allegation. Figure (a) is based on federal expenditures, whereas Figures (b) is based on state expenditures. Figure (c) is based on total foster care program expenditures, which include any costs related to CPS investigation and foster care programs, including administrative and training expenses as well as foster care maintenance costs. Figure (d) is based on foster care administrative expenditures, which cover caseworker salaries, staff training, case planning and pre-placement activities, and information technology systems. Regressions are weighted by child population.

Figure 11 presents the trends in maltreatment allegations per 10,000 children and foster care expenditures per child from 2006 to 2016, separately for total foster care program expenditures and administrative expenditures. While maltreatment allegations exhibit an upward trend following the 2010 reformulation, foster care expenditures remained flat or showed a slight decline. These trends suggest that despite the rising demands for child

Table 5: Difference-in-Differences Results for Child Welfare Expenditures per Allegation

	(1) Total	(2) Federal	(3) State	(4) Total Foster Care	(5) Administrative Foster Care
Post × Exp_s	-946.33	-503.69**	-500.44	-240.08***	-155.87***
	(639.34)	(227.44)	(588.56)	(68.62)	(45.56)
	[-6.7%]	[-7.8%]	[-6.5%]	[-12.8%]	[-14.5%]
Mean	14080	6444.44	7671.23	1869.93	1075.07
R-Squared	0.833	0.819	0.811	0.805	0.830
Observations	234	234	234	234	234
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
X_{st}	Yes	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 6, where the dependent variables are child welfare expenditures per allegation. Column (1) is based on total expenditures, whereas Columns (2) and (3) are based on federal and state expenditures, respectively. Column (4) is based on total foster care program expenditures, and Column (5) is based on foster care administrative expenditures. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in the pre-reformulation period (2006-2009) are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

maltreatment investigations and protective services, the resources devoted to these activities did not keep pace with increasing needs.

To analyze the causal impacts of the reformulation on child welfare expenditures, I estimate the following equation.

$$y_{st} = \beta \times \text{Post} \times \text{Exp}_s + \alpha_s + \gamma_t + X'_{st}\gamma + \epsilon_{st} \tag{6}$$

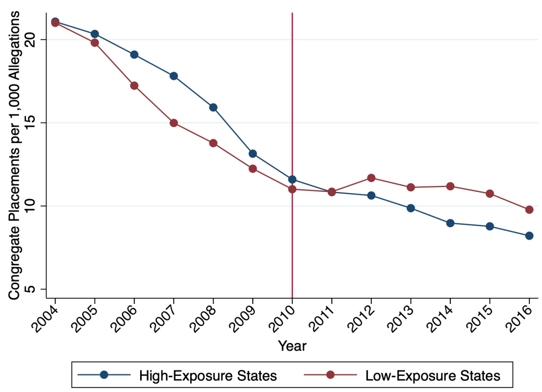
where $t \in \{2006, 2008, 2010, 2012, 2014, 2016\}$ and Post is an indicator variable for years after 2010. Figure 12 and Table 5 show that expenditures from federal funds decreased by \$504 per allegation, representing an 7.8% decline from the pre-reformulation period. Expenditures on the total foster care program and on foster care administration fell by \$240 and \$156 per allegation, corresponding to declines of 12.8% and 14.5% from their respective baseline means.

The decline in federal expenditures per allegation following the reformulation aligns with broader fiscal pressures. Under the 2011 Budget Control Act, sequestration took effect in 2013 after Congress failed to enact a deficit-reduction plan, triggering automatic across-the-board cuts. Flexible federal streams were reduced, constraining the federal share of child welfare spending while maltreatment risk from the opioid epidemic was intensifying. As a result, agencies operated with fewer resources per case, a constraint that is consistent with the observed rise in false negatives.

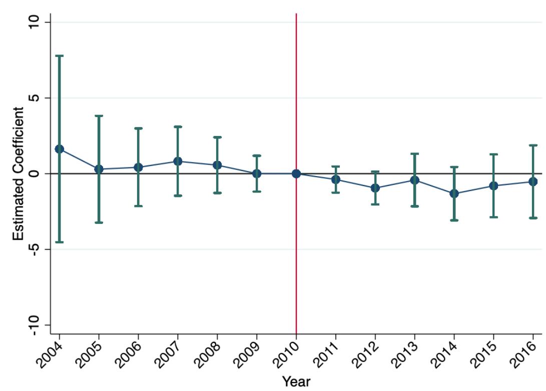
6.C Foster Homes

A shortage of available foster homes can constrain CPS's response capacity. I provide suggestive evidence on the role of foster home supply in shaping the response to the opioid epidemic. 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 13: 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 the median. Figure (b) 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, where the dependent variable is congregate placements per 1,000 allegations. Regressions are weighted by child population.

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,

Table 6: Difference-in-Differences Results for Congregate Placement Rate

	(1)
Pre-reformulation	0.59
	(1.27)
Short-run	-0.58
	(0.57)
	[-5.2%]
Medium-run	-0.87
	(0.98)
	[-7.8%]
Mean	11.22
R-Squared	0.86
Observations	506
State FE	Yes
Year FE	Yes
X_{st}	Yes

Notes. This table reports point estimates and standard errors from Equation 4, 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Armstrong and Dollard, 2011). Figure 13a shows these trends, with congregate placements per 1,000 allegations declining in both high- and low-exposure states. The frequency with which CPS resorts to congregate care therefore reflects pressures on foster home capacity. Measuring congregate placements per 1,000 allegations conditions on the flow of cases entering the system and indicates whether CPS had to rely more heavily on congregate care to absorb rising demand. In this way, the measure serves as an indirect indicator of foster home supply constraints: increasing congregate placement rates would indicate greater strain on the foster home capacity while decreasing rates would imply that the constrains have been eased.

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 13b and Table 6 presents the event study and difference-in-differences results for congregate placements rates. The congregate placement rate remained stable following the reformulation, suggesting that a foster home shortage has not been the primary driver of CPS responses.

7 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 well-documented 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 Schedule II prescription opioids per capita, I show that the opioid epidemic led to an increase in maltreatment allegations. Despite heightened risk, institutional responses did not scale protective actions accordingly, leading to an increase the reinvestigations of children who were not initially placed in foster care. Foster care placement rates remained unchanged and administrative expenditures per allegation declined, pointing at limited systemic adjustment.

The findings of this paper uncover the impacts of the opioid epidemic on child welfare as well as its ripple 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, these results suggest that the opioid epidemic can have long-lasting intergenerational impacts.

Finally, this paper highlights the importance of institutional responsiveness in times of crisis. Greater flexibility in placement norms would allow CPS to adjust protective decisions as maltreatment risk changes, while funding mechanisms that respond to changes in caseloads, through contingency funds or formulas that scale with demand, would allow agencies to mobilize resources effectively. Such funds could support timely hiring and training of staff, expansion of preventive services, and improvements in investigative capacity. At the state level, allocating resources in a manner responsive to rising demand for protective services is essential. More broadly, aligning child protection systems with fluctuations in child maltreatment risk is critical to mitigating the long-term consequences of unaddressed maltreatment.

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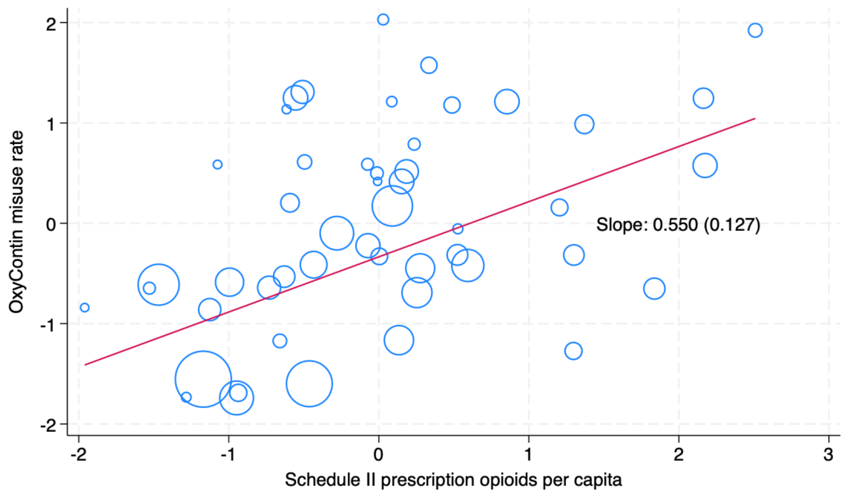
Appendix

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

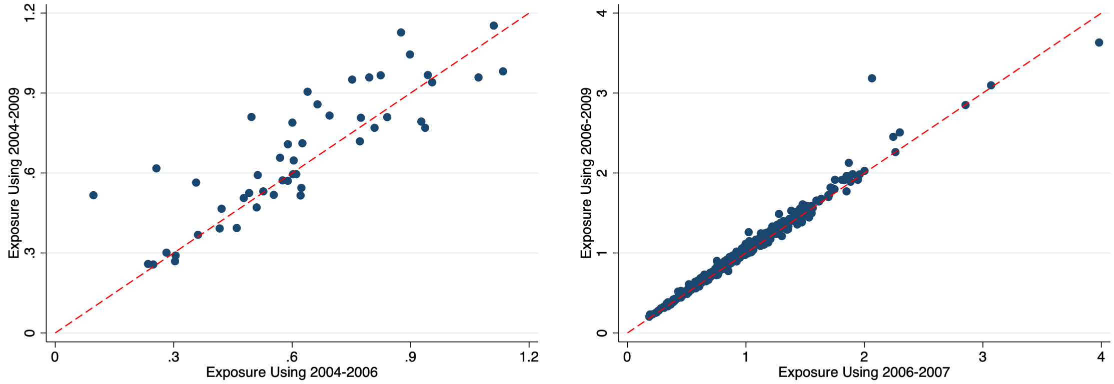
Jeongsoo Suh

Figure A1: Correlation Between Standardized State- and County-Level Exposures



Notes. This figure illustrates the correlation between standardized state- and county-level exposures. The state-level exposure is the pre-reformulation OxyContin misuse rate. The county-level exposure is pre-reformulation Schedule II prescriptions per capita, aggregated to the state level using county population weights. The red line denotes the weighted least squares fit, weighted by average state population from 2006–2009.

Figure A2: Comparison of Primary and Alternative Exposure Measures



(a) State

(b) County

Notes. This figure plots the alternative exposure measures against primary exposure measures computed using different years of data. The x-axis represents the alternative measures, and the y-axis represents the primary measures. The primary state-level exposure measure is computed using 2004–2009 data on OxyContin misuse, while the alternative measure is based on 2004–2006 data. The primary county-level exposure measure is computed using 2006–2009 data on Schedule II prescription opioids per capita, while the alternative measure is based on 2006–2007 data. The dotted line represents the 45-degree line.

Table A1: First Stage Regressions

	(1) State	(2) State	(3) County	(4) County
Exposure	-0.18***	-0.15***	-0.11***	-0.06**
	(0.05)	(0.04)	(0.02)	(0.02)
Unemployment		0.04		0.03*
		(0.03)		(0.01)
Labor Force Participation		0.04***		0.01***
		(0.01)		(0.00)
Percent Black		0.02***		0.01***
		(0.01)		(0.00)
Percent Female		-0.02		-0.03*
		(0.10)		(0.02)
Percent Child		-0.05		-0.01
		(0.03)		(0.01)
Constant	-0.16***	-0.84	-0.12***	0.52
	(0.04)	(5.34)	(0.02)	(0.88)
R-Squared	0.33	0.60	0.07	0.26
F Statistics	16.30	12.66	20.52	19.42
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.

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

Table A2: Covariate Balance

	(1) Unemployment Rate	(2) LFP Rate	(3) Percent Black	(4) Percent Female	(5) Percent Child
Panel A: State					
OxyContin Misuse	0.90	0.83	0.50	-0.06	-0.05
	(0.94)	(0.82)	(0.57)	(0.08)	(0.28)
Constant	2.70***	-1.27**	-0.20	-0.03	-0.81***
	(0.67)	(0.58)	(0.40)	(0.06)	(0.20)
Observations	49	49	49	49	49
R-Squared	0.02	0.02	0.02	0.01	0.00
Panel B: County					
Prescription Opioids	0.26	0.03	0.04	-0.09***	0.13***
	(0.37)	(0.38)	(0.06)	(0.02)	(0.04)
Constant	4.24***	-0.91**	0.16*	0.07***	-0.30***
	(0.50)	(0.36)	(0.08)	(0.03)	(0.05)
Observations	643	643	643	643	643
R-Squared	0.00	0.00	0.00	0.04	0.07

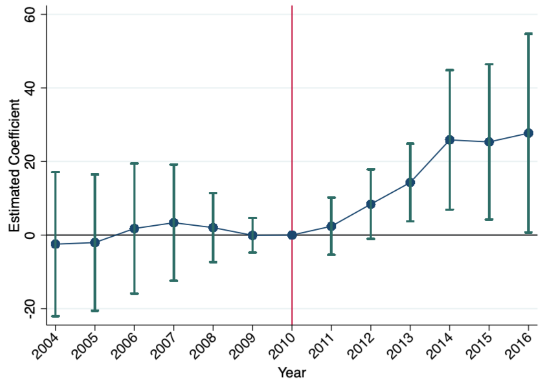
Notes. This table reports the results of regressing the changes in state and county covariates on pre-reformulation OxyContin misuse rate and Schedule II opioid prescriptions per capita. Changes in state-level covariates are measured from 2004 to 2009, while changes in county-level covariates are measured from 2006 to 2009. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Summary Statistics for Maltreatment Allegations

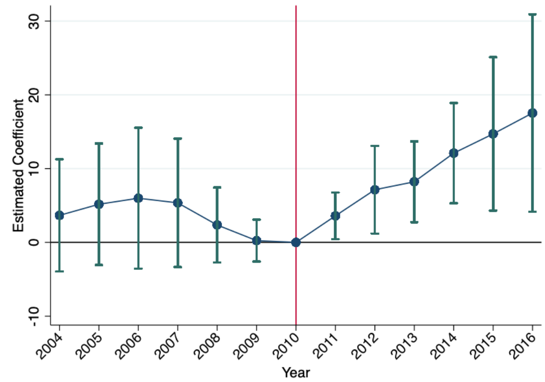
Variable	All Allegations	Professional Allegations
Panel A: Maltreatment Types		
Neglect	60.4	53.1
Physical Abuse	21.8	24.1
Sexual Abuse	7.5	8.4
Psychological/Emotional Maltreatment	6.9	7.0
Medical Neglect	2.4	2.7
Other	9.5	9.1
Panel B: Child Charateristics		
White	60.0	58.5
Black	25.4	26.0
Male	49.6	49.6
Female	49.8	49.9
Young (age < 7)	45.8	43.3
Old (age ≥ 7)	53.5	56.3
Panel C: Report Sources		
Education Personnel	16.7	29.6
Legal Personnel	16.5	29.4
Social Services Personnel	10.2	18.2
Medical Personnel	7.5	13.3
Mental Health Personnel	4.7	8.3
Child Daycare Provider	0.7	1.2
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.

Figure A3: Allegations by Type of Maltreatment - State



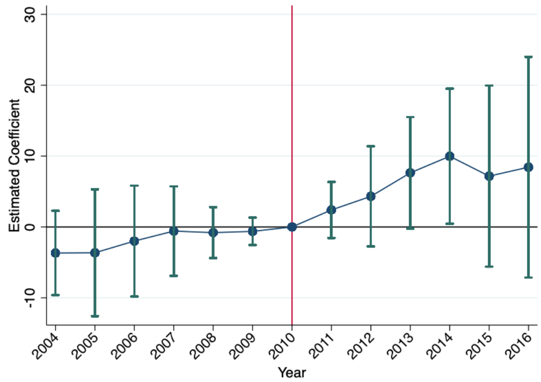
(a) Neglect



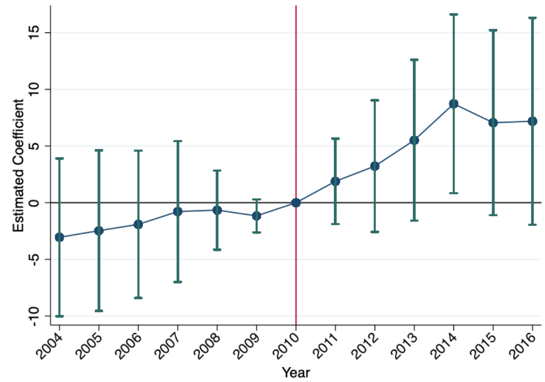
(b) Physical Abuse

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 that are adjusted for within-state clustering. Dependent variables are neglect and physical abuse per 10,000 children. Regressions are weighted by child population.

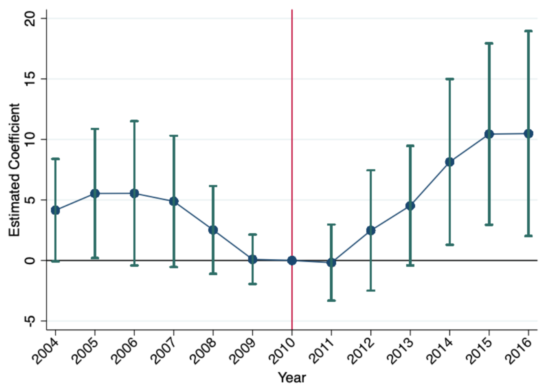
Figure A4: Allegations by Source of Report - State



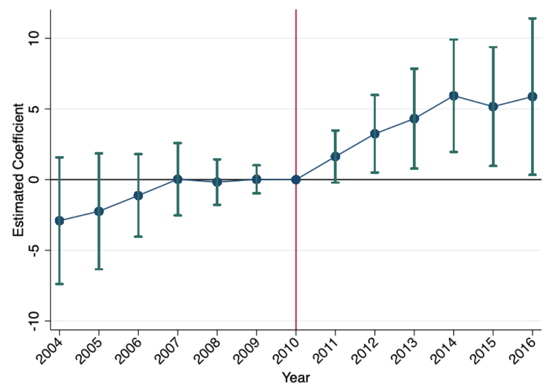
(a) Education Personnel



(b) Legal Personnel



(c) Social Services Personnel



(d) Medical Personnel

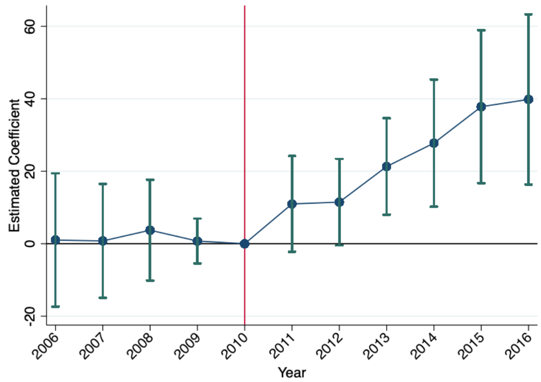
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 10,000 children reported by education, legal, social services, and medical personnel. Regressions are weighted by child population.

Table A4: Allegations by Type of Maltreatment and Source of Report - State

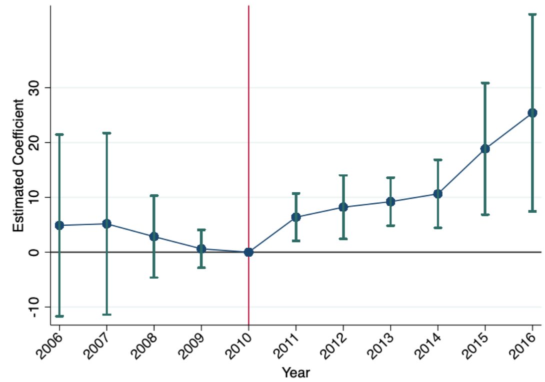
	(1) Neglect	(2) Physical	(3) Education	(4) Legal	(5) Social Services	(6) Medical
Pre-reformulation	0.51	3.66	-1.78	-1.60	3.65*	-0.98
	(6.46)	(3.19)	(2.56)	(2.28)	(1.94)	(1.17)
Short-run	8.26**	6.32***	4.72	3.50	2.28	3.02**
	(3.71)	(2.27)	(2.87)	(2.64)	(1.97)	(1.19)
	[6.2%]	[10.4%]	[6.9%]	[4.9%]	[5.0%]	[9.6%]
Medium-run	26.04**	14.73***	8.40	7.58*	9.66**	5.57**
	(10.90)	(4.91)	(6.25)	(4.11)	(3.69)	(2.18)
	[19.7%]	[24.1%]	[12.3%]	[10.6%]	[21.1%]	[17.7%]
Mean	132.37	61.05	68.39	71.22	45.8	31.46
R-Squared	0.83	0.68	0.83	0.92	0.84	0.85
Observations	634	634	634	634	634	634
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 per 10,000 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A5: Allegations by Type of Maltreatment - County



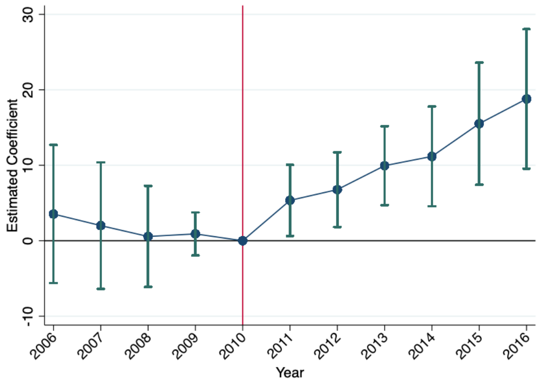
(a) Neglect



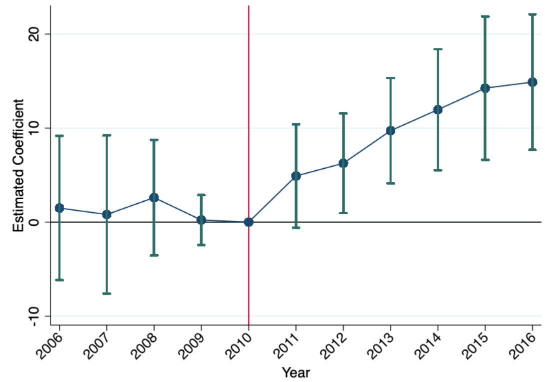
(b) Physical Abuse

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 3 that are adjusted for within-state clustering. Dependent variables are neglect and physical abuse per 10,000 children. Regressions are weighted by child population.

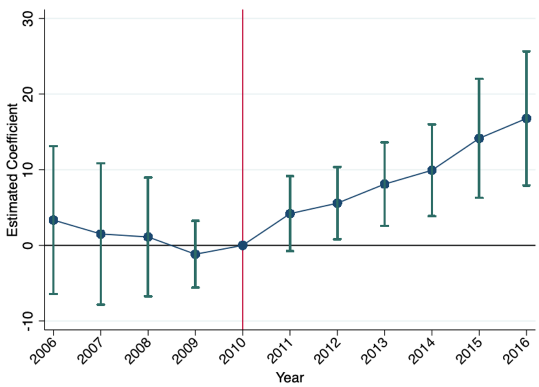
Figure A6: Allegations by Source of Report - County



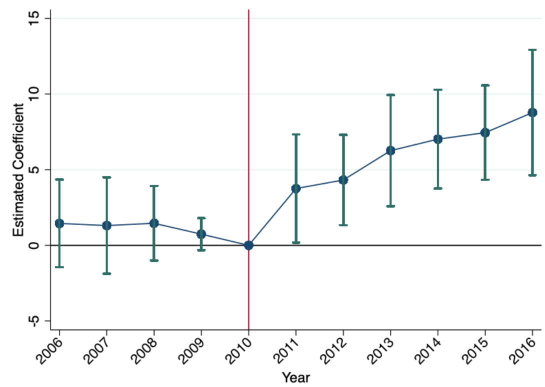
(a) Education Personnel



(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 3 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 10,000 children reported by education, legal, social services, and medical personnel. Regressions are weighted by child population.

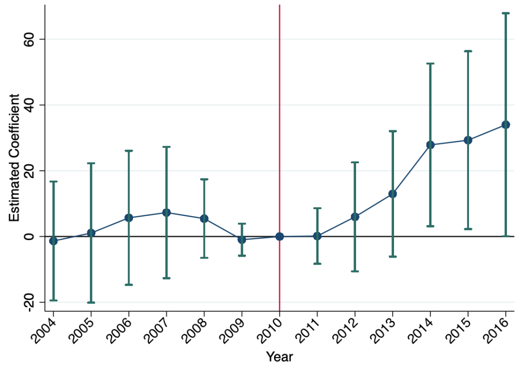
Table A5: Allegations by Type of Maltreatment and Source of Report - County

	(1) Neglect	(2) Physical	(3) Education	(4) Legal	(5) Social Services	(6) Medical
Pre-reformulation	1.61	3.33	1.73	1.30	1.16	1.24
	(6.25)	(5.37)	(3.16)	(3.00)	(3.76)	(1.11)
Short-run	14.56**	7.92***	7.34***	6.94**	5.94**	4.77***
	(6.04)	(2.21)	(2.19)	(2.62)	(2.43)	(1.66)
	[11.0%]	[13.0%]	[10.7%]	[9.7%]	[13.0%]	[15.2%]
Medium-run	34.91***	18.15***	15.07***	13.63***	13.54***	7.72***
	(9.48)	(5.71)	(3.72)	(3.51)	(3.63)	(1.53)
	[26.4%]	[29.7%]	[22.0%]	[19.1%]	[29.6%]	[24.5%]
Mean	132.37	61.05	68.39	71.22	45.8	31.46
R-Squared	0.85	0.70	0.81	0.90	0.84	0.85
Observations	7073	7073	7073	7073	7073	7073
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

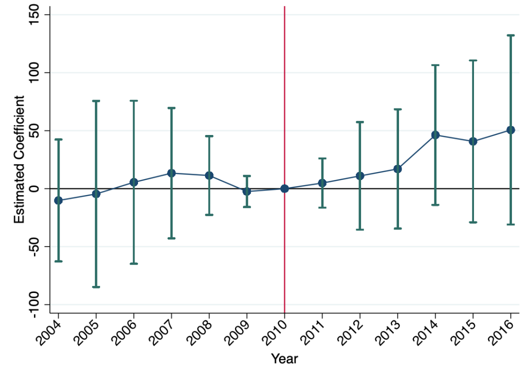
Notes. This table reports point estimates and standard errors from Equation 5, where dependent variables are maltreatment allegations per 10,000 children, broken down by report type and source. Regressions are weighted by child population. Percentage changes from the baseline mean in 2010 are reported in square brackets.

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

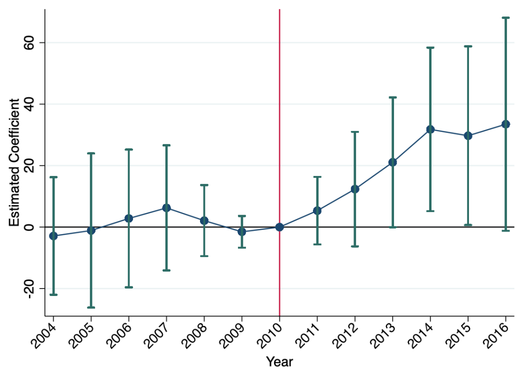
Figure A7: Maltreatment Allegations by Child Characteristics - State



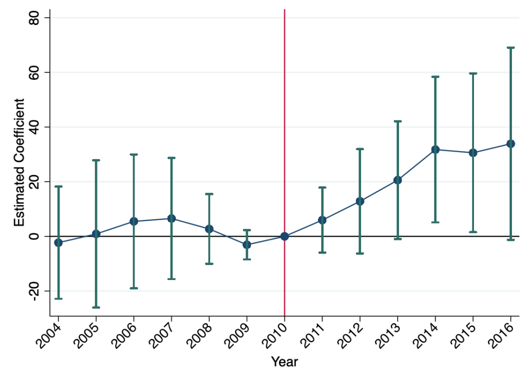
(a) White



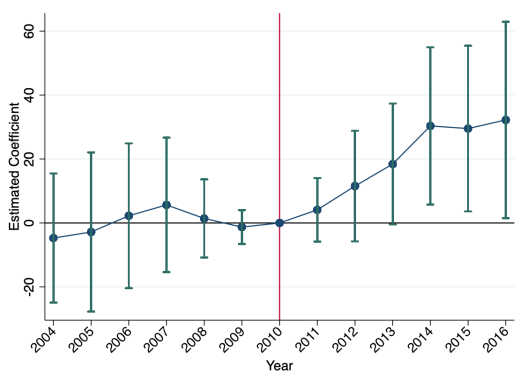
(b) Black



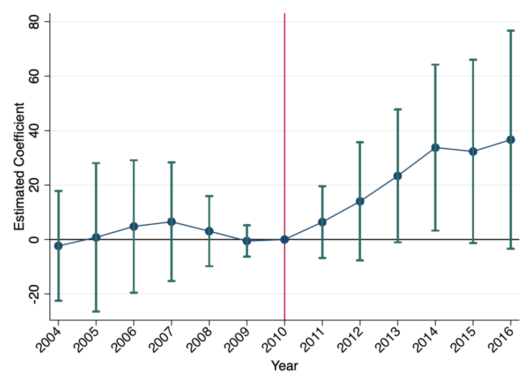
(c) Male



(d) Female



(e) Young



(f) Old

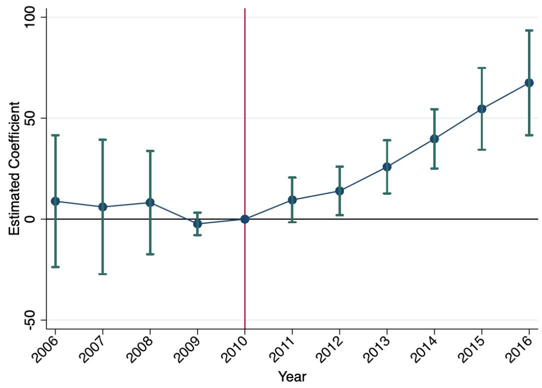
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 10,000 children, broken down by child characteristics. Regressions are weighted by child population.

Table A6: Maltreatment Allegations by Child Characteristics - State

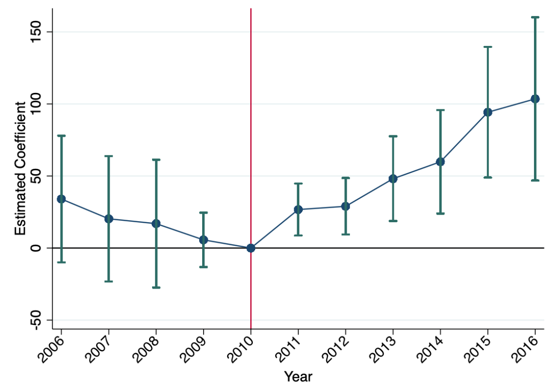
	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
Pre-reformulation	2.85	2.42	0.99	1.67	0.16	2.20
	(7.03)	(23.24)	(7.41)	(8.09)	(7.85)	(8.13)
Short-run	6.26	10.87	12.79	13.03	10.89	14.72
	(6.62)	(17.86)	(7.69)	(8.00)	(7.09)	(8.88)
	[3.1%]	[2.6%]	[5.3%]	[5.1%]	[4.6%]	[5.8%]
Medium-run	30.12**	45.63	31.36**	31.79**	29.68**	34.43*
	(13.93)	(34.84)	(14.72)	(14.81)	(13.02)	(17.19)
	[14.9%]	[10.8%]	[13.1%]	[12.5%]	[12.5%]	[13.5%]
Mean	201.76	422.01	240.21	253.54	237.13	254.85
R-Squared	0.86	0.86	0.87	0.87	0.87	0.87
Observations	621	621	634	634	634	634
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 per 10,000 children, 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

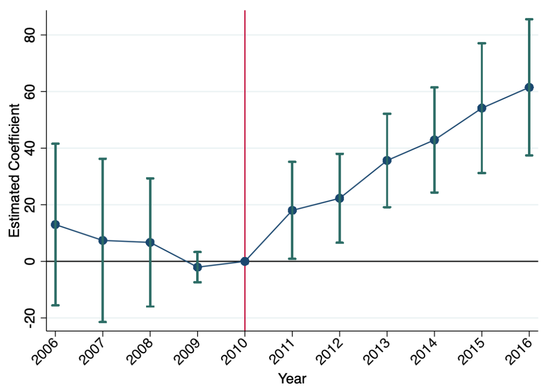
Figure A8: Maltreatment Allegations by Child Characteristics - County



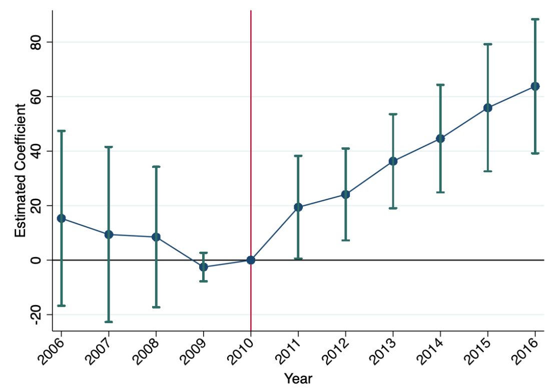
(a) White



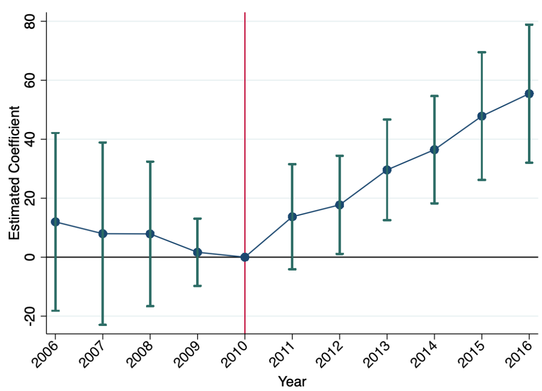
(b) Black



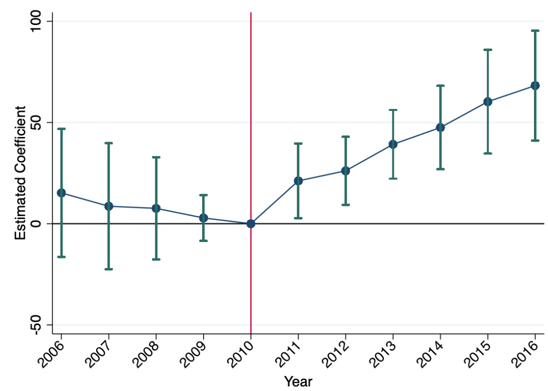
(c) Male



(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 3 that are adjusted for within-state clustering. Dependent variables are maltreatment allegations per 10,000 children, broken down by child charateristics. Regressions are weighted by child population.

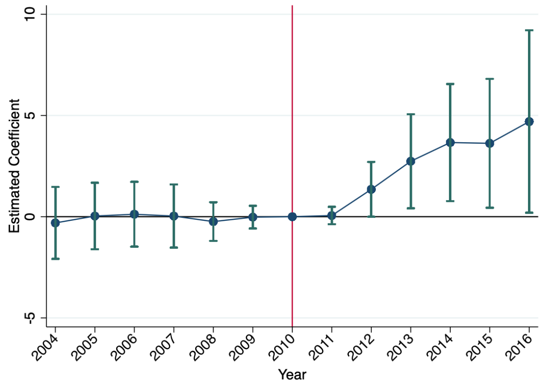
Table A7: Maltreatment Allegations by Child Characteristics - County

	(1) White	(2) Black	(3) Male	(4) Female	(5) Young	(6) Old
Pre-reformulation	5.18	18.74	6.16	7.49	7.16	8.66
	(11.86)	(17.24)	(9.95)	(11.20)	(11.76)	(11.96)
Short-run	16.35***	34.40***	25.23***	26.56***	19.88**	29.10***
	(4.70)	(9.00)	(7.66)	(8.38)	(8.20)	(8.04)
	[8.1%]	[8.2%]	[10.5%]	[10.5%]	[8.4%]	[11.4%]
Medium-run	53.56***	84.76***	52.59***	54.54***	45.62***	58.89***
	(9.60)	(20.92)	(10.42)	(10.71)	(9.89)	(11.80)
	[26.5%]	[20.1%]	[21.9%]	[21.5%]	[19.2%]	[23.1%]
Mean	201.76	422.01	240.21	253.54	237.13	254.85
R-Squared	0.87	0.87	0.87	0.86	0.88	0.85
Observations	6952	6952	7073	7073	7073	7073
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

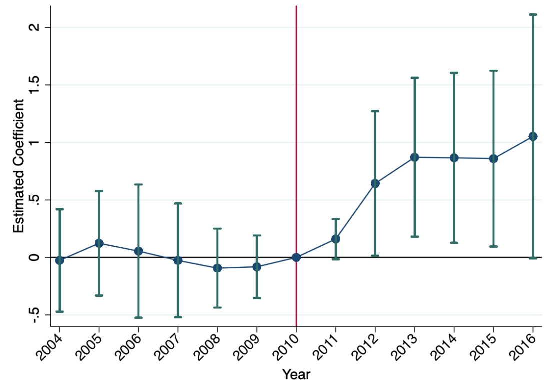
Notes. This table reports point estimates and standard errors from Equation 5, where the dependent variables are maltreatment allegations per 10,000 children, broken down by child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.

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

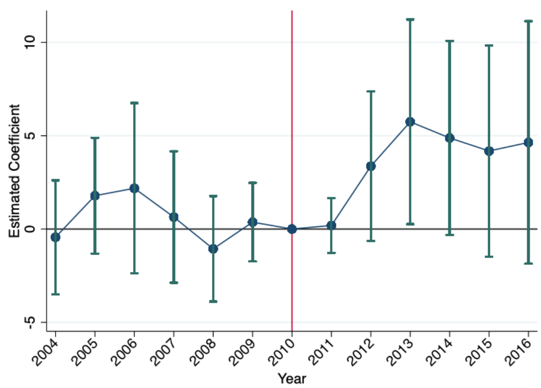
Figure A9: False Negative Rate by Type of Maltreatment - State



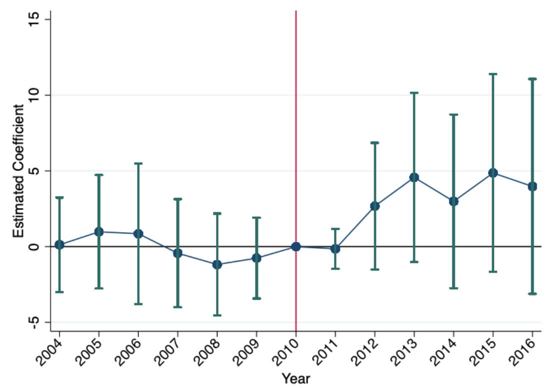
(a) Neglect, per 10K Children



(b) Physical Abuse, per 10K Children



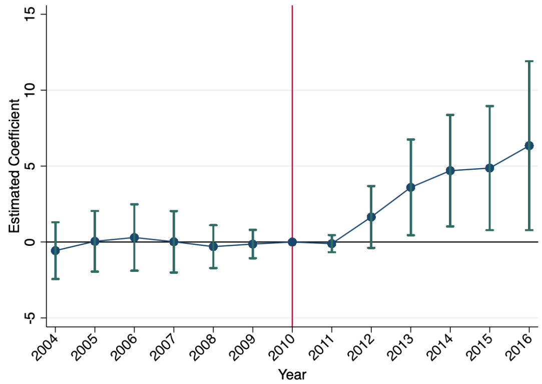
(c) Neglect, per 1K Allegations



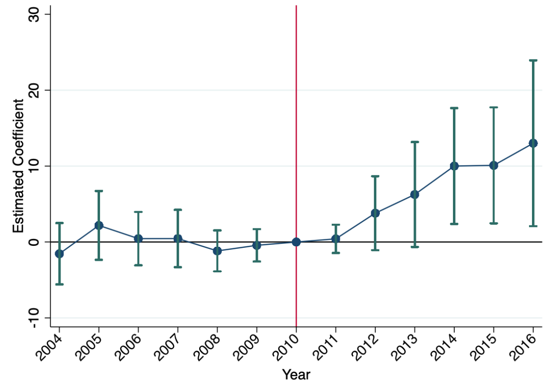
(d) Physical Abuse, per 1K Allegations

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 type of maltreatment. Regressions are weighted by child population.

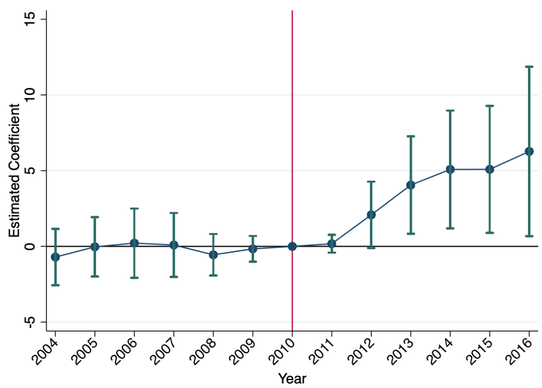
Figure A10: False Negatives per 10K Children by Child Characteristics - State



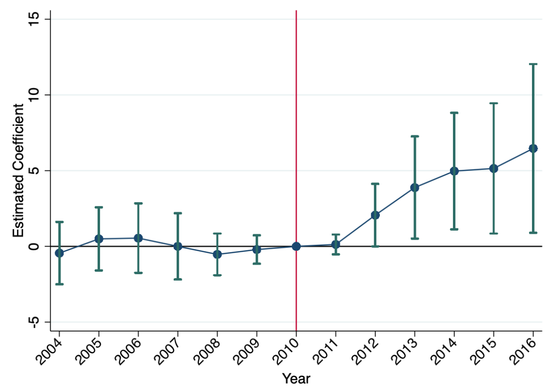
(a) White



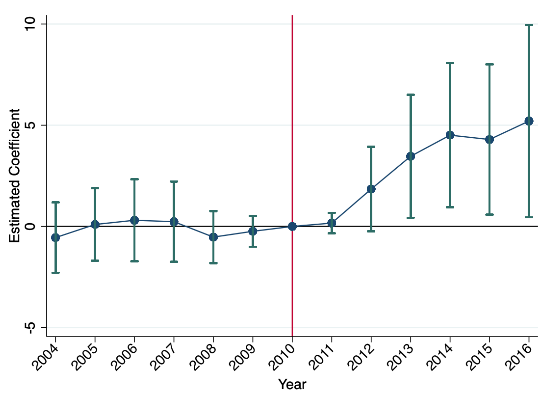
(b) Black



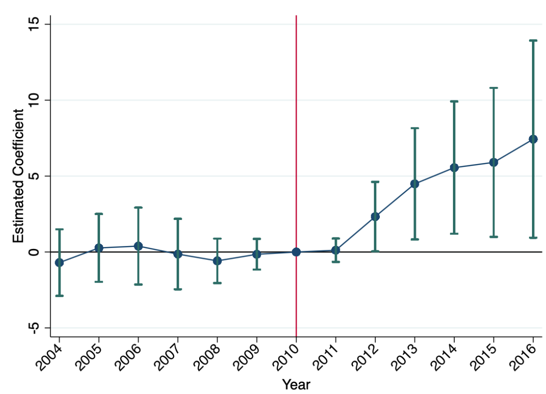
(c) Male



(d) Female



(e) Young



(f) Old

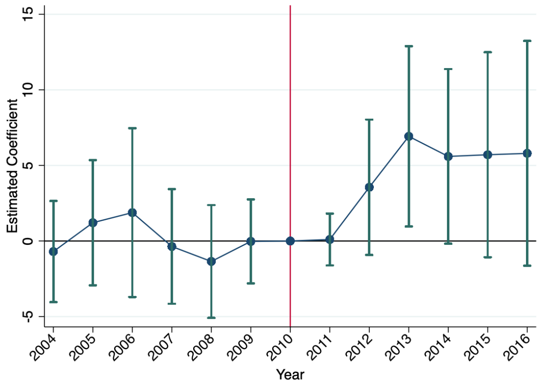
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 that are adjusted for within-state clustering. Dependent variables are false negatives per 10,000 children by child characteristics. Regressions are weighted by child population.

Table A8: False Negatives per 10K Children by Type and Child Characteristics - State

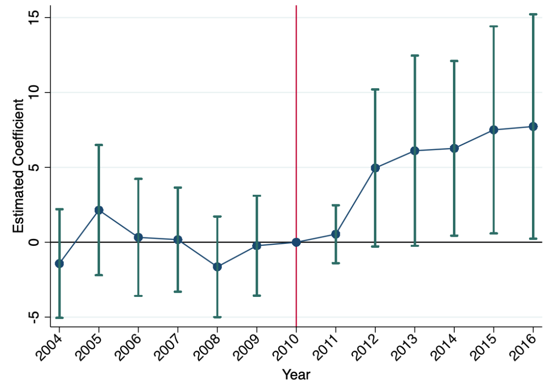
	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	-0.01	-0.00	-0.13	-0.08	-0.21	-0.06	-0.13	-0.18
	(0.06)	(0.02)	(0.75)	(1.23)	(0.73)	(0.76)	(0.66)	(0.83)
Short-run	0.14**	0.06**	1.68*	3.45*	2.07**	2.00**	1.80**	2.28**
	(0.06)	(0.02)	(0.86)	(2.00)	(0.91)	(0.90)	(0.87)	(0.98)
	[1.8%]	[1.6%]	[14.1%]	[13.0%]	[14.4%]	[13.2%]	[13.5%]	[14.3%]
Medium-run	0.39**	0.09**	5.19**	10.86**	5.36**	5.42**	4.57**	6.17**
	(0.17)	(0.04)	(2.12)	(4.18)	(2.19)	(2.19)	(1.90)	(2.53)
	[4.9%]	[2.3%]	[43.7%]	[41.0%]	[37.2%]	[35.8%]	[34.2%]	[38.6%]
Mean	7.93	3.84	11.89	26.52	14.4	15.13	13.36	15.97
R-Squared	0.772	0.374	0.883	0.301	0.717	0.719	0.604	0.831
Observations	506	506	506	506	506	506	506	506
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4, where the dependent variables are false negatives per 10,000 children by type of maltreatment 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

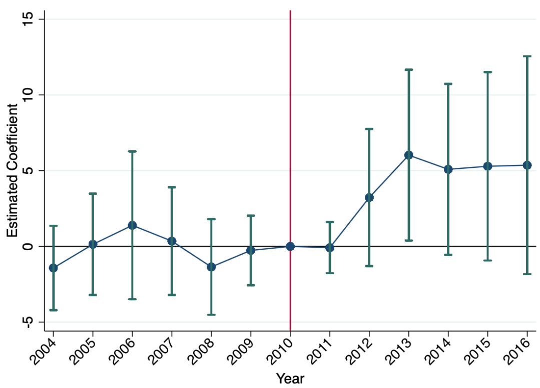
Figure A11: False Negatives per 1K Allegations by Child Characteristics - State



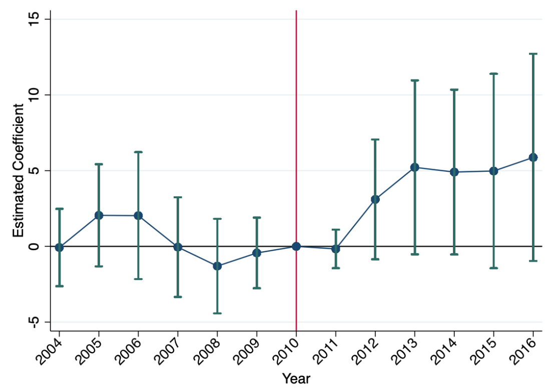
(a) White



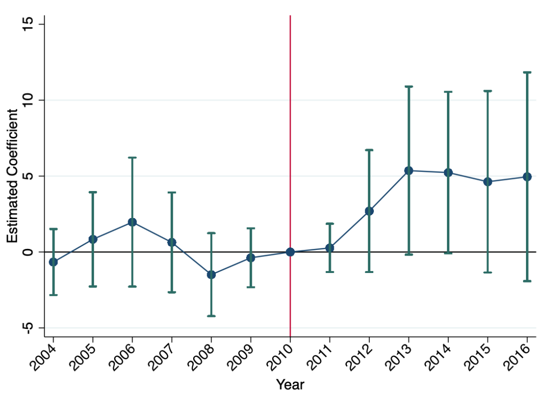
(b) Black



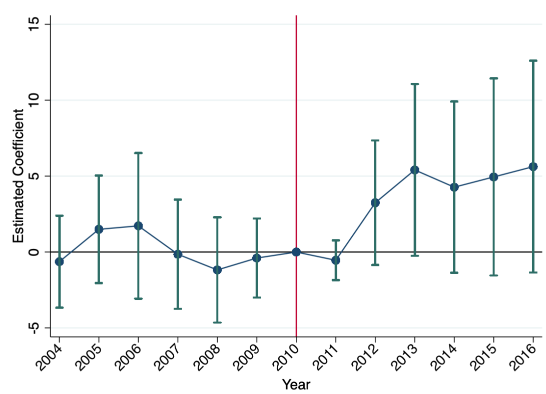
(c) Male



(d) Female



(e) Young



(f) Old

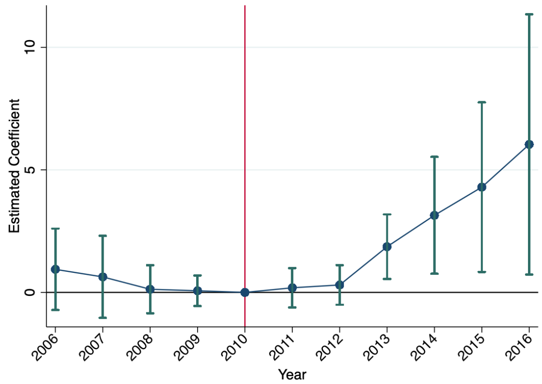
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations by child characteristics. Regressions are weighted by child population.

Table A9: False Negatives per 1K Allegations by Type and Child Characteristics - State

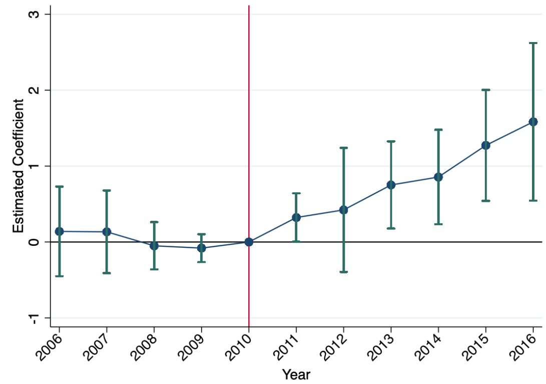
	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.49	-0.16	0.05	-0.17	-0.24	0.28	0.09	0.06
	(1.26)	(1.53)	(1.66)	(1.37)	(1.43)	(1.27)	(1.14)	(1.51)
Short-run	3.07*	2.28	3.48*	3.83*	3.01*	2.70	2.75	2.67
	(1.63)	(1.70)	(1.79)	(1.98)	(1.78)	(1.65)	(1.71)	(1.60)
	[5.1%]	[3.7%]	[5.5%]	[5.9%]	[4.8%]	[4.4%]	[4.7%]	[4.1%]
Medium-run	4.45	3.81	5.52*	7.00**	5.06	5.12*	4.81	4.79
	(2.72)	(3.07)	(3.15)	(3.21)	(3.03)	(2.96)	(2.89)	(3.02)
	[7.3%]	[6.2%]	[8.7%]	[10.7%]	[8.1%]	[8.3%]	[8.3%]	[7.3%]
Mean	60.63	61.03	63.47	65.23	62.4	61.74	58.26	65.29
R-Squared	0.75	0.73	0.76	0.72	0.76	0.77	0.77	0.76
Observations	506	506	506	506	506	506	506	506
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4, where the dependent variables are false negatives per 1,000 allegations by maltreatment types and child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

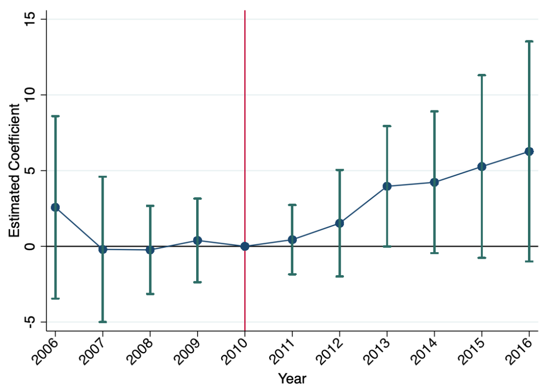
Figure A12: False Negative Rate by Maltreatment Type - County



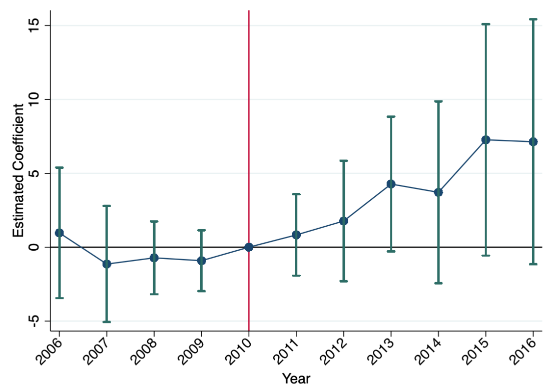
(a) Neglect, per 10K Children



(b) Physical Abuse, per 10K Children



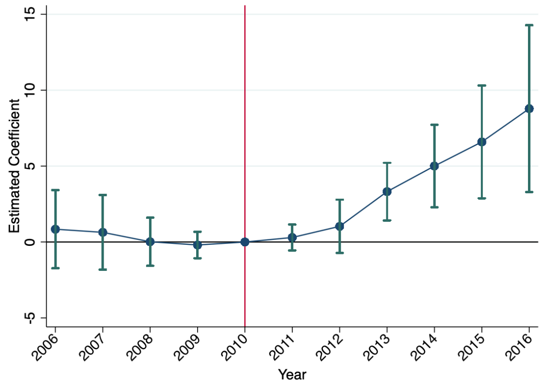
(c) Neglect, per 1K Allegations



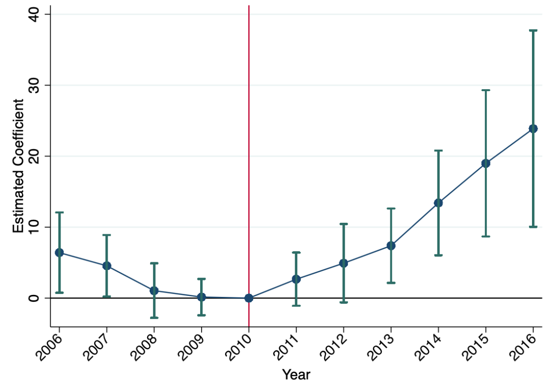
(d) Physical Abuse, per 1K Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 3 that are adjusted for within-state clustering. Dependent variables are false negative rates by type of maltreatment. Regressions are weighted by child population.

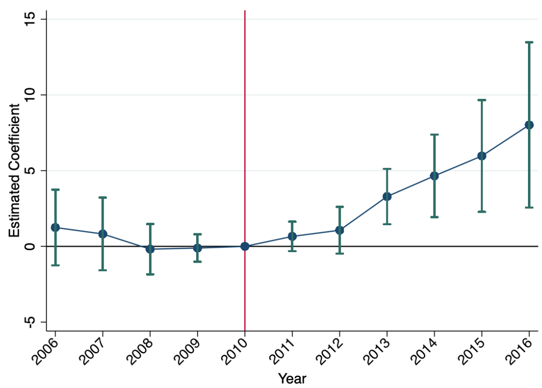
Figure A13: False Negatives per 10K Children by Child Characteristics - County



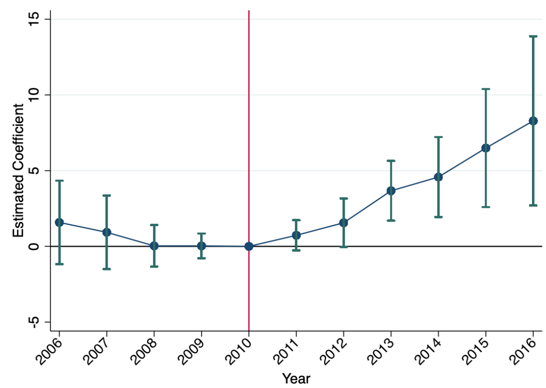
(a) White



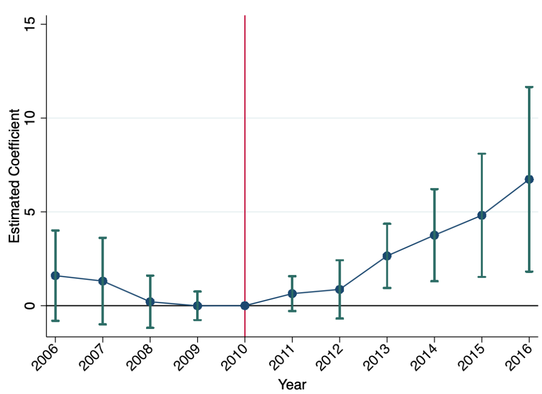
(b) Black



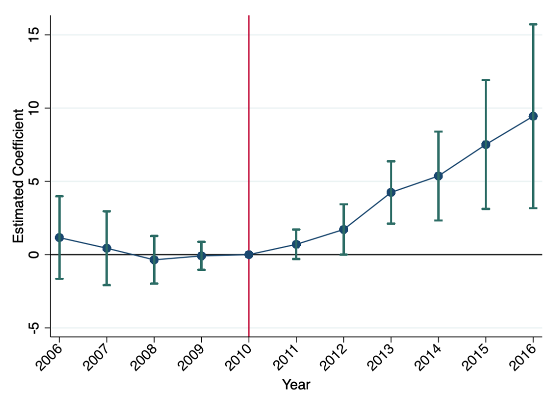
(c) Male



(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 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 10,000 children by child characteristics. Regressions are weighted by child population.

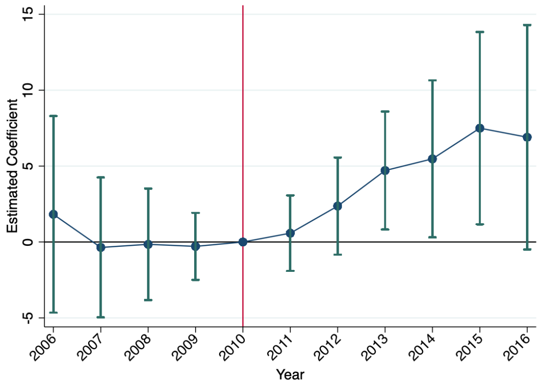
Table A10: False Negatives per 10K Children by Type and Child Characteristics - County

	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.04	0.00	0.30	2.91*	0.41	0.61	0.74	0.26
	(0.05)	(0.02)	(0.84)	(1.44)	(0.83)	(0.82)	(0.74)	(0.89)
Short-run	0.08**	0.05*	1.52**	4.98**	1.66***	1.97***	1.38**	2.19***
	(0.03)	(0.03)	(0.60)	(1.95)	(0.57)	(0.56)	(0.56)	(0.59)
	[1.0%]	[1.3%]	[12.8%]	[18.8%]	[11.5%]	[13.0%]	[10.3%]	[13.7%]
Medium-run	0.44**	0.12***	6.70***	18.62***	6.14***	6.37***	5.05***	7.34***
	(0.19)	(0.04)	(1.95)	(5.12)	(1.95)	(1.99)	(1.74)	(2.26)
	[5.5%]	[3.1%]	[56.3%]	[70.2%]	[42.6%]	[42.1%]	[37.8%]	[46.0%]
Mean	7.93	3.84	11.89	26.52	14.4	15.13	13.36	15.97
R-Squared	0.68	0.67	0.72	0.60	0.70	0.70	0.70	0.71
Observations	4587	4587	4587	4587	4587	4587	4587	4587
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

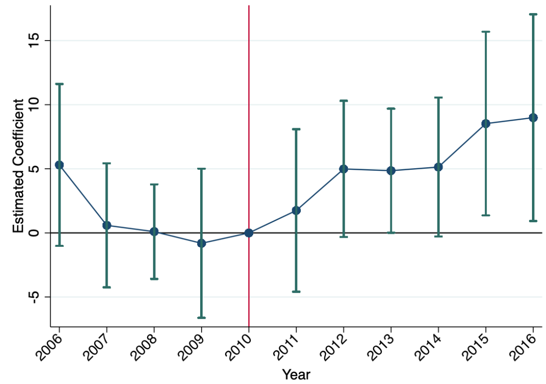
Notes. This table reports point estimates and standard errors from Equation 4, where the dependent variables are false negatives per 10,000 children by type of maltreatment and child characteristics. Regressions are weighted by child population. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.

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

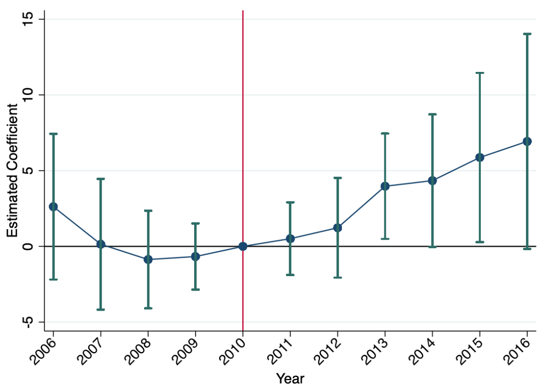
Figure A14: False Negatives per 1K Allegations by Child Characteristics - County



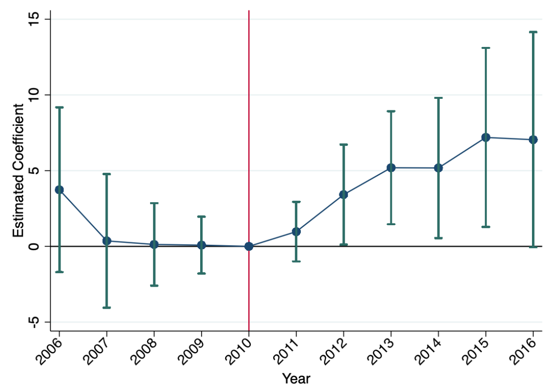
(a) White



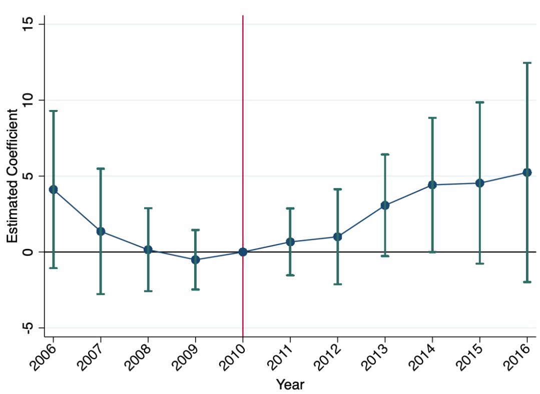
(b) Black



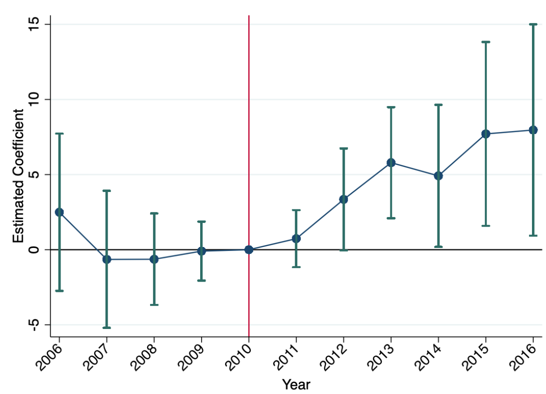
(c) Male



(d) Female



(e) Young



(f) Old

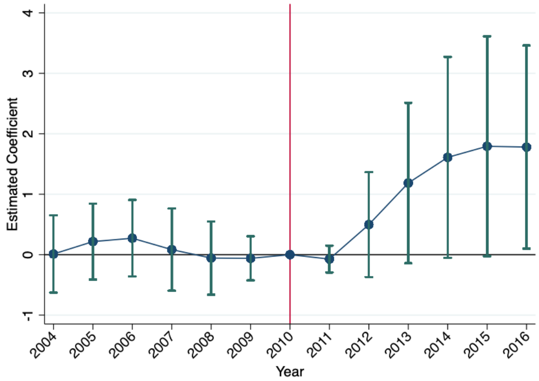
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations by child characteristics. Regressions are weighted by child population.

Table A11: False Negatives per 1K Allegations by Type and Child Characteristics - County

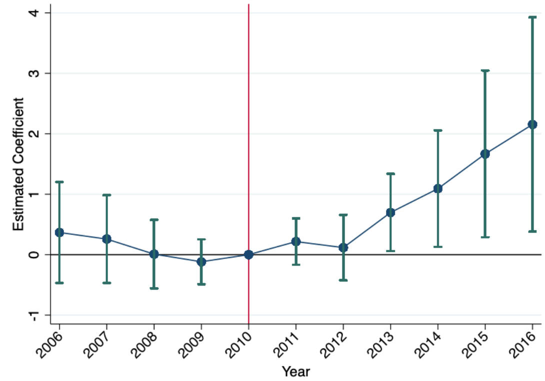
	(1) Neglect	(2) Physical	(3) White	(4) Black	(5) Male	(6) Female	(7) Young	(8) Old
Pre-reformulation	0.60	-0.48	0.23	1.22	0.25	1.02	1.20	0.24
	(1.79)	(1.07)	(1.85)	(1.73)	(1.50)	(1.51)	(1.37)	(1.56)
Short-run	1.95	2.27	2.51*	3.82**	1.89	3.16**	1.58	3.24***
	(1.35)	(1.67)	(1.25)	(1.71)	(1.26)	(1.20)	(1.18)	(1.16)
	[3.2%]	[3.7%]	[4.0%]	[5.9%]	[3.0%]	[5.1%]	[2.7%]	[5.0%]
Medium-run	5.17*	5.95	6.53**	7.45**	5.64**	6.37**	4.70*	6.73**
	(2.90)	(3.65)	(2.95)	(3.21)	(2.77)	(2.85)	(2.73)	(2.91)
	[8.5%]	[9.7%]	[10.3%]	[11.4%]	[9.0%]	[10.3%]	[8.1%]	[10.3%]
Mean	60.63	61.03	63.47	65.23	62.4	61.74	58.26	65.29
R-Squared	0.64	0.57	0.67	0.37	0.67	0.67	0.68	0.65
Observations	4587	4587	4587	4587	4587	4587	4587	4587
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 5, where the dependent variables are maltreatment allegations 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

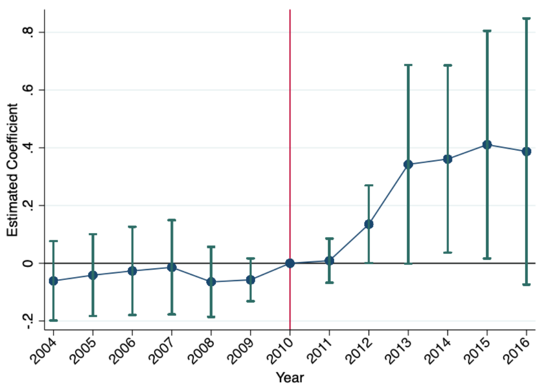
Figure A15: False Negatives Based on Alternative Measures - Per 10K Children



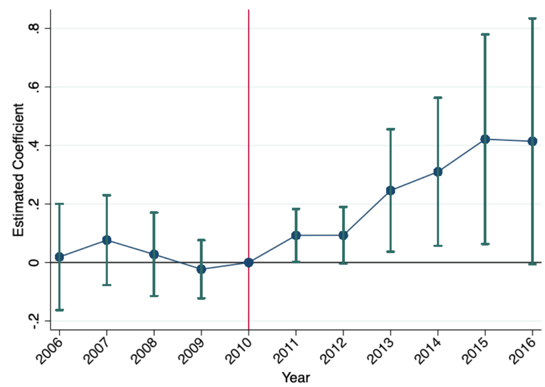
(a) State, Substantiation



(b) County, Substantiation



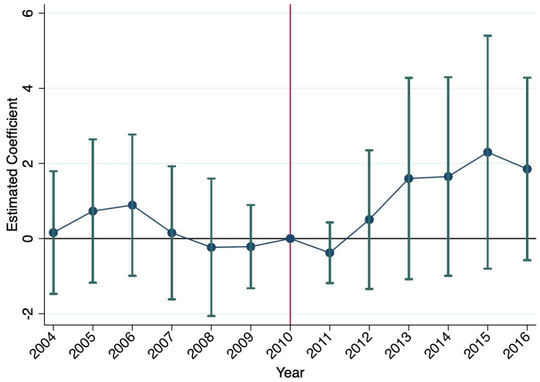
(c) State, Foster Care



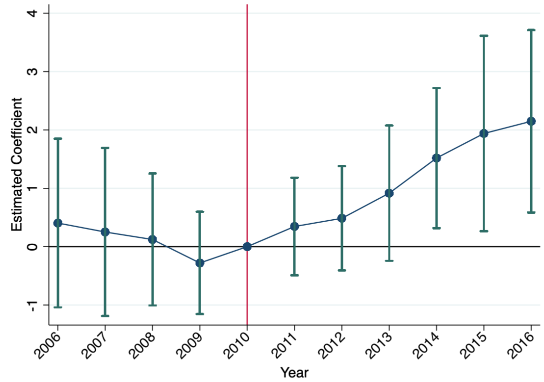
(d) County, Foster Care

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 10,000 children based on alternative measures. In Figures (a) and (b), false negatives refer to cases in which children were reinvestigated and substantiated within six months after not being placed in foster care following the initial investigation. In Figures (c) and (d), false negatives refer to cases in which children were reinvestigated and placed in foster care within six months after not being placed in foster care following the initial investigation. Figures (a) and (c) are state-level results whereas Figures (b) and (d) are county-level results. Regressions are weighted by child population.

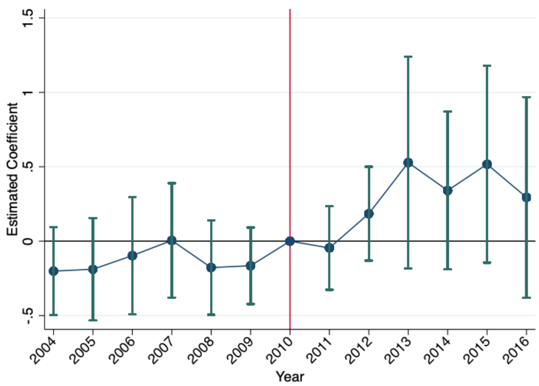
Figure A16: False Negatives Based on Alternative Measures - Per 1K Allegations



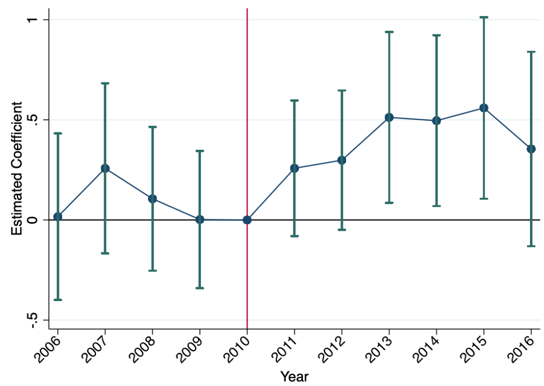
(a) State, Substantiation



(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 2 and Equation 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations based on alternative measures. In Figures (a) and (b), false negatives refer to cases in which children were reinvestigated and substantiated within six months after not being placed in foster care following the initial investigation. In Figures (c) and (d), false negatives refer to cases in which children were reinvestigated and placed in foster care within six months after not being placed in foster care following the initial investigation. Figures (a) and (c) are state-level results whereas Figures (b) and (d) are county-level results. Regressions are weighted by child population.

Table A12: Difference-in-Differences Results for False Negatives per 10K Children Based on Alternative Measures

	(1) State Substantiation	(2) State Foster Care	(3) County Substantiation	(4) County Foster Care
Pre-reformulation	0.07	-0.05	0.12	0.02
	(0.26)	(0.06)	(0.28)	(0.06)
Short-run	0.53	0.16*	0.34*	0.14***
	(0.38)	(0.08)	(0.20)	(0.05)
	[14.0%]	[18.0%]	[9.3%]	[15.7%]
Medium-run	1.70**	0.38*	1.62**	0.38**
	(0.82)	(0.19)	(0.67)	(0.16)
	[45.0%]	[42.7%]	[42.9%]	[41.6%]
Mean	3.78	0.89	3.78	0.89
R-Squared	0.75	0.68	0.70	0.56
Observations	506	506	4587	4587
State or County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

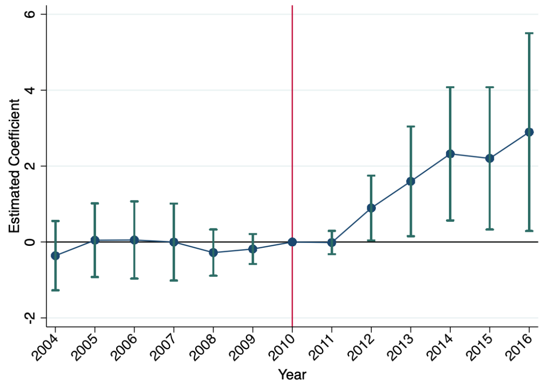
Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where the dependent variables are false negatives per 10,000 children by alternative measures. In Columns (1) and (3), false negatives refer to cases in which children were reinvestigated and substantiated within six months after not being placed in foster care following the initial investigation. In Columns (2) and (4), false negatives refer to cases in which children were reinvestigated and placed in foster care within six months after not being placed in foster care following the initial investigation. 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 A13: Difference-in-Differences Results for False Negatives per 1K Allegations by Alternative Measures

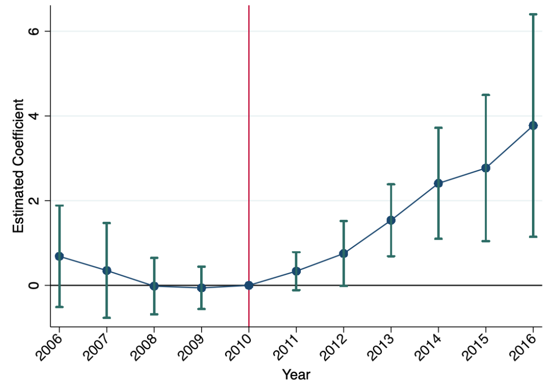
	(1) State Substantiation	(2) State Foster Care	(3) County Substantiation	(4) County Foster Care
Pre-reformulation	0.21	-0.14	0.11	0.09
	(0.74)	(0.13)	(0.53)	(0.15)
Short-run	0.57	0.22	0.58	0.35**
	(0.84)	(0.19)	(0.38)	(0.15)
	[3.5%]	[5.7%]	[3.6%]	[9.1%]
Medium-run	1.89	0.37	1.86***	0.47**
	(1.30)	(0.29)	(0.70)	(0.20)
	[11.6%]	[9.6%]	[11.4%]	[12.2%]
Mean	16.26	3.84	16.26	3.84
R-Squared	0.86	0.74	0.78	0.52
Observations	506	506	4587	4587
State or County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes

Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where The dependent variables are false negatives per 1,000 allegations by alternative measures. In Columns (1) and (3), false negatives refer to cases in which children were reinvestigated and substantiated within six months after not being placed in foster care following the initial investigation. In Columns (2) and (4), false negatives refer to cases in which children were reinvestigated and placed in foster care within six months after not being placed in foster care following the initial investigation. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

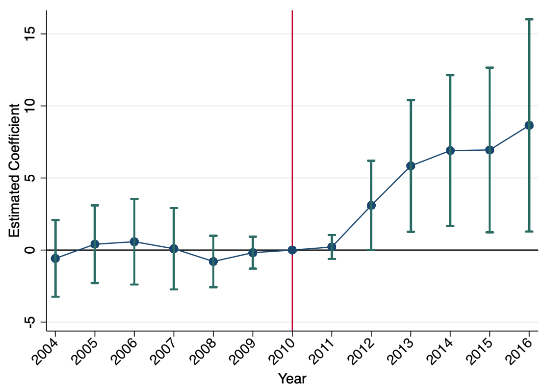
Figure A17: False Negatives Based on Alternative Time Frames - Per 10K Children



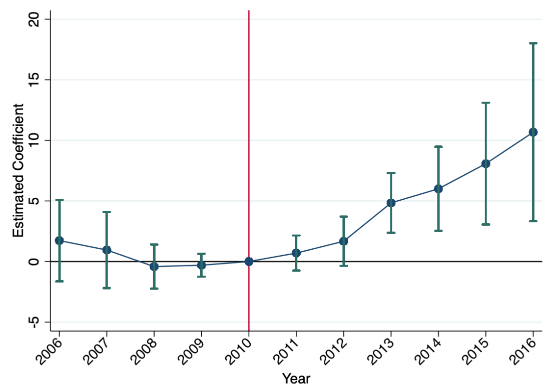
(a) State, 3 Months



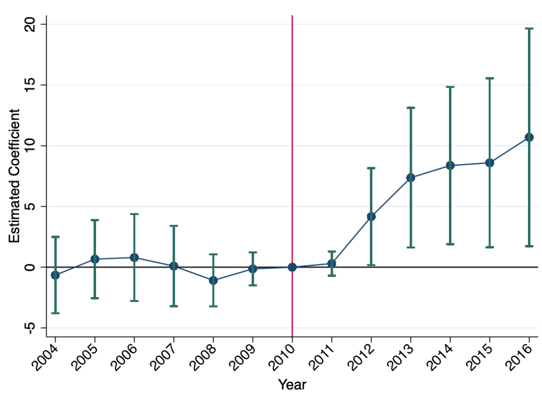
(b) County, 3 Months



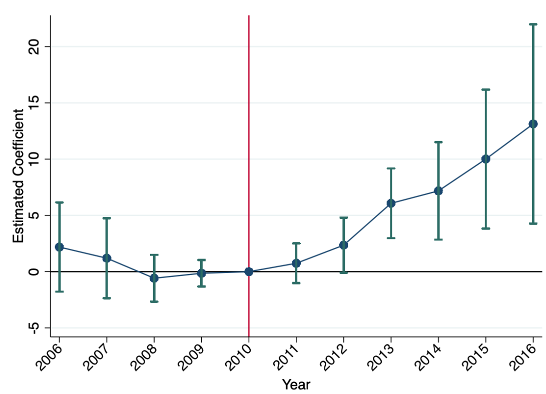
(c) State, 9 Months



(d) County, 9 Months



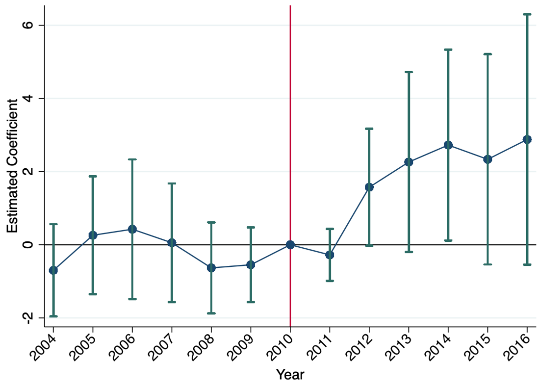
(e) State, 12 Months



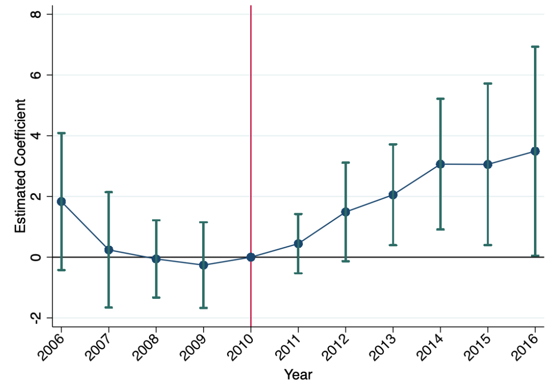
(f) County, 12 Months

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 10,000 children based on alternative time frames between the focal and subsequent investigation. Regressions are weighted by child population.

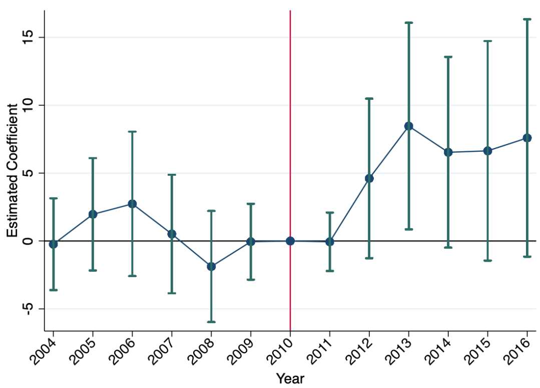
Figure A18: False Negatives Based on Alternative Time Frames - Per 1K Allegations



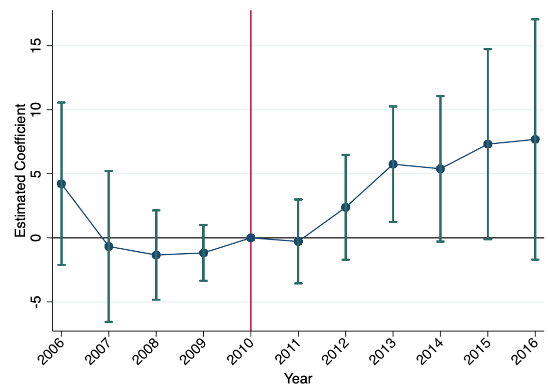
(a) State, 3 Months



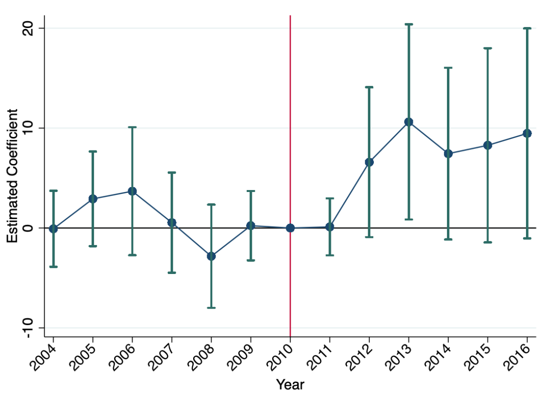
(b) County, 3 Months



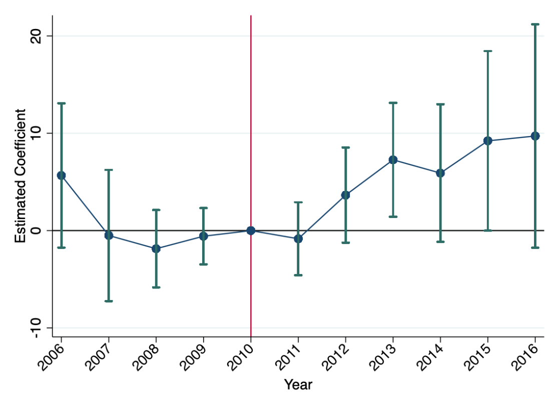
(c) State, 9 Months



(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 2 and Equation 3 that are adjusted for within-state clustering. Dependent variables are false negatives per 1,000 allegations based on alternative time frames between the focal and subsequent investigation. Regressions are weighted by child population.

Table A14: Difference-in-Differences Results for False Negatives by Time Frame - Per 10K Children

	(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	-0.13	-0.14	-0.14	0.23	0.43	0.59
	(0.34)	(0.94)	(1.11)	(0.37)	(1.03)	(1.17)
Short-run	0.84**	3.03**	3.91**	0.87***	2.35***	2.99***
	(0.39)	(1.27)	(1.62)	(0.26)	(0.74)	(0.91)
	[14.7%]	[14.8%]	[15.1%]	[15.1%]	[11.5%]	[11.6%]
Medium-run	2.46**	7.39**	9.06**	2.95***	8.12***	9.93***
	(1.01)	(2.94)	(3.59)	(0.93)	(2.59)	(3.19)
	[43.2%]	[36.0%]	[34.9%]	[51.8%]	[39.6%]	[38.4%]
Mean	5.7	20.52	25.93	5.7	20.52	25.93
R-Squared	0.72	0.74	0.75	0.68	0.72	0.73
Observations	506	506	506	4587	4587	4587
State or County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5, where the dependent variables are false negatives per 10,000 children based on alternative time frames between the focal and subsequent investigation. 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 A15: Difference-in-Differences Results for False Negatives by Time Frame - Per 1K Allegations

	(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	-0.22	0.41	0.60	0.41	0.17	0.58
	(0.61)	(1.66)	(1.93)	(0.67)	(1.79)	(1.99)
Short-run	1.17	4.29*	5.72*	1.32**	2.57*	3.29*
	(0.71)	(2.32)	(3.01)	(0.58)	(1.47)	(1.77)
	[4.8%]	[4.9%]	[5.1%]	[5.4%]	[2.9%]	[2.9%]
Medium-run	2.57*	6.70*	8.12*	3.17**	6.67*	8.09*
	(1.42)	(3.78)	(4.58)	(1.35)	(3.64)	(4.54)
	[10.5%]	[7.6%]	[7.3%]	[12.9%]	[7.6%]	[7.3%]
Mean	24.52	88.29	111.54	24.52	88.29	111.54
R-Squared	0.77	0.77	0.77	0.67	0.71	0.72
Observations	506	506	506	4587	4587	4587
State of County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

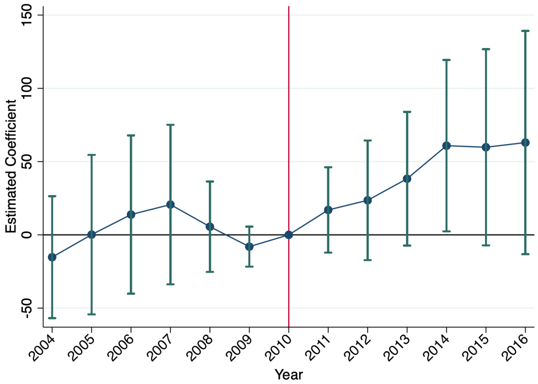
Notes. This table reports point estimates and standard errors from Equation 4 and Equation 5, where the dependent variables are false negatives per 1,000 allegations based on alternative time frames between the focal and subsequent investigation. Columns (1), (2), and (3) are state-level results whereas 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 A16: Difference-in-Differences Results for Binned Treatment

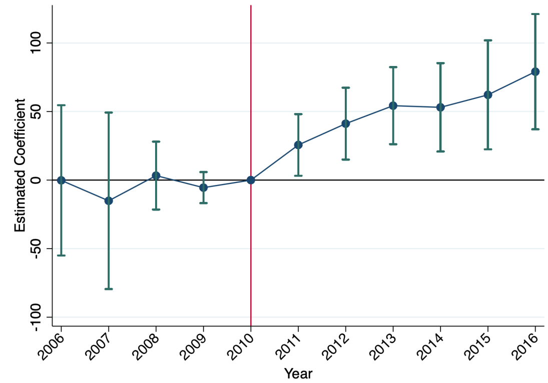
	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
PreQ2	0.803	0.309	0.028	0.049	-3.267	-0.302
	(1.617)	(0.625)	(0.121)	(0.063)	(3.484)	(1.708)
PreQ3	1.270	-1.208	-0.291	-0.009	-5.518	-0.056
	(2.476)	(1.965)	(0.208)	(0.096)	(3.359)	(2.175)
PreQ4	0.039	1.487	0.055	0.061	1.779	0.224
	(2.298)	(2.764)	(0.178)	(0.202)	(3.352)	(3.400)
SrQ2	-2.065	1.553**	0.105	0.157	1.887	1.074
	(1.899)	(0.680)	(0.158)	(0.099)	(2.667)	(1.457)
SrQ3	2.152	4.441***	0.184	0.274	0.614	3.575
	(2.650)	(1.222)	(0.179)	(0.164)	(2.905)	(2.846)
SrQ4	2.026	4.958**	0.657**	0.385***	9.643*	5.007*
	(2.491)	(2.329)	(0.295)	(0.134)	(5.357)	(2.564)
MrQ2	-2.951	3.387**	0.163	0.327*	0.808	2.334
	(3.066)	(1.373)	(0.305)	(0.170)	(4.778)	(2.310)
MrQ3	1.670	6.606***	0.229	0.872*	-1.253	7.763
	(3.799)	(2.403)	(0.428)	(0.442)	(5.211)	(5.429)
MrQ4	9.653*	10.330***	1.862**	1.361***	18.515*	13.365*
	(4.894)	(2.993)	(0.750)	(0.447)	(10.253)	(6.975)
R-Squared	0.879	0.869	0.756	0.712	0.779	0.705
Observations	634	7073	506	4587	506	4587
State or County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
X_{st} or X_{ct}	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table reports coefficients and standard errors from regressions where the treatment variable is divided into quartiles. The first quartile serves as the reference group. PreQN denotes the pre-reformulation coefficient for the Nth quartile group, SrQN denotes the short-run coefficient for the Nth quartile group, and MrQN denotes the medium-run coefficient for the Nth quartile group. Standard errors in parentheses are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

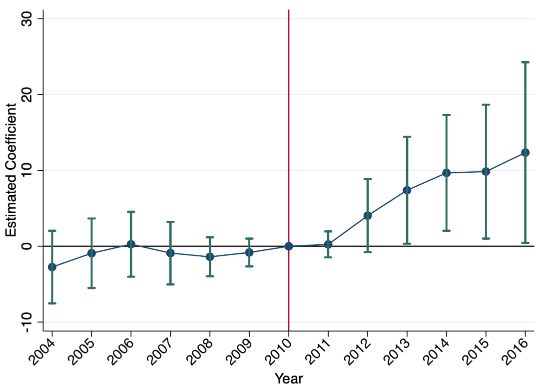
Figure A19: Event Study Results for Binary Treatment



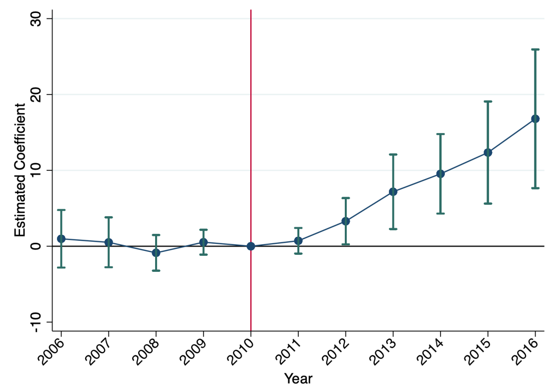
(a) Allegations by State



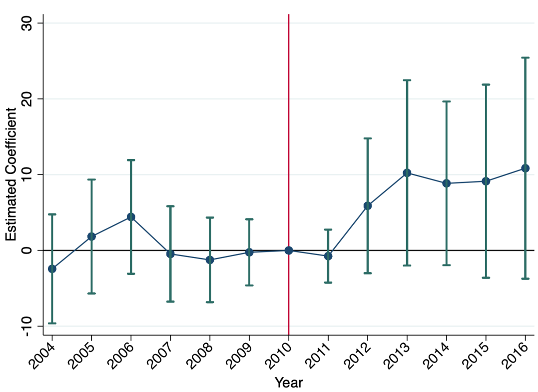
(b) Allegations by County



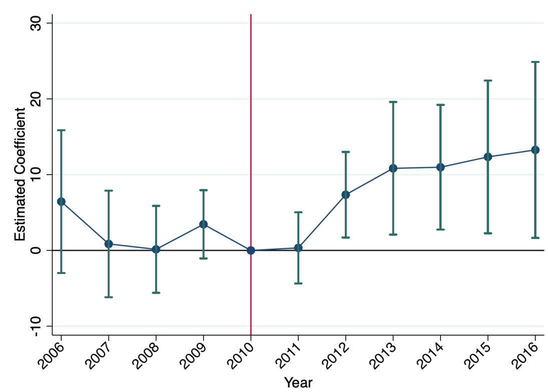
(c) FN by State, per 10K Children



(d) FN by County, per 10K Children



(e) FN by State, per 1K Allegations



(f) FN by County, per 1K Allegations

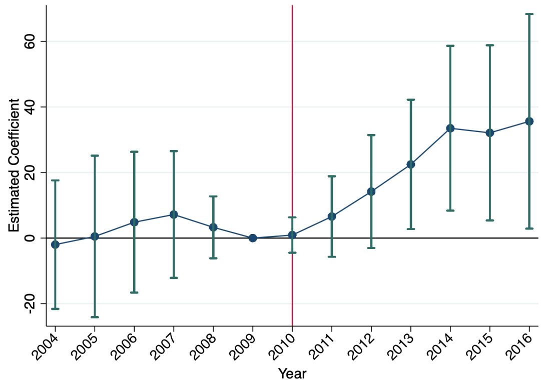
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Figures (a) and (b) report results for allegations. Figures (c), (d), (e), and (f) report results for false negatives. Figures (a), (c), and (e) are based on state-level analyses, whereas Figures (b), (d), and (f) are based on county-level analyses. Regressions are weighted by child population.

Table A17: Difference-in-Differences Results for Binary Treatment

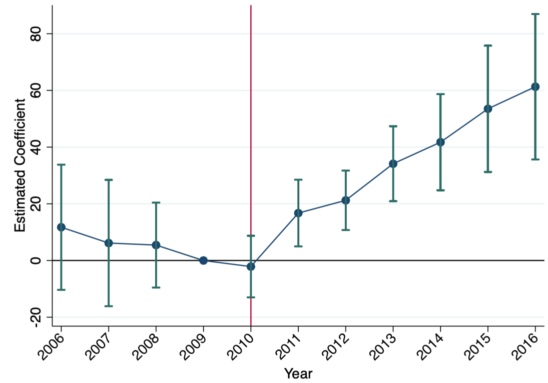
	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
Pre-reformulation	2.85	-4.40	-1.10	-0.00	0.24	0.20
	(18.21)	(17.52)	(1.57)	(0.99)	(2.67)	(1.50)
Short-run	26.23	40.18***	3.86*	2.38**	5.10	3.49**
	(17.35)	(11.91)	(2.00)	(1.10)	(3.71)	(1.60)
	[10.9%]	[16.8%]	[26.1%]	[16.1%]	[8.2%]	[5.6%]
Medium-run	61.02*	64.43***	10.51**	8.82**	9.46	8.50***
	(33.53)	(18.70)	(4.63)	(3.54)	(6.21)	(2.93)
	[25.5%]	[26.9%]	[71.1%]	[59.7%]	[15.3%]	[13.7%]
Mean	239.76	239.76	14.78	14.78	61.84	61.84
R-Squared	0.87	0.87	0.73	0.71	0.77	0.70
Observations	634	7073	506	4587	506	4587
State or County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5. Columns (1) and (2) report results for allegations. Columns (3), (4), (5), and (6) report results for false negatives. Columns (1), (3), and (5) are based on state-level analyses, whereas Columns (2), (4), and (6) are based on county-level analyses. Dependent variables in Columns (1), (2), (3) and (4) are measured per 10,000 children. Dependent variables in Columns (5) and (6) are measured 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

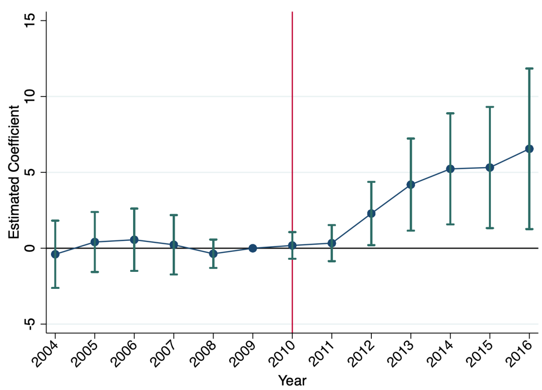
Figure A20: Event Study Results for 2009 Normalized



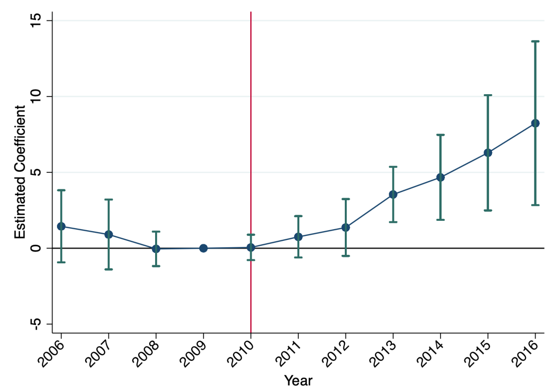
(a) Allegations by State



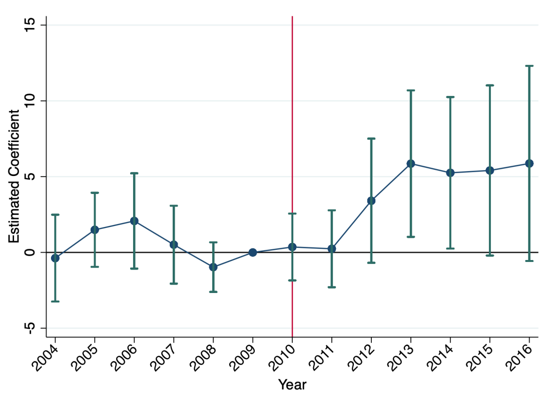
(b) Allegations by County



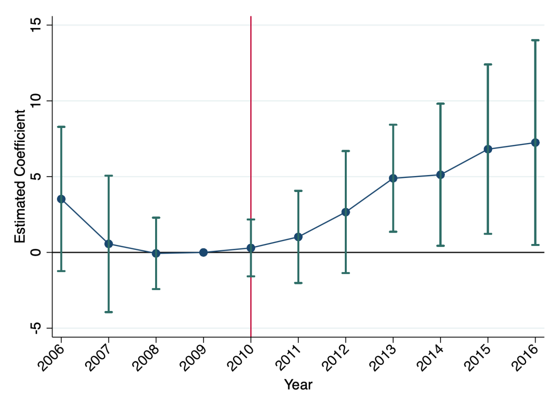
(c) FN by State, per 10K Children



(d) FN by County, per 10K Children



(e) FN by State, per 1K Allegations



(f) FN by County, per 1K Allegations

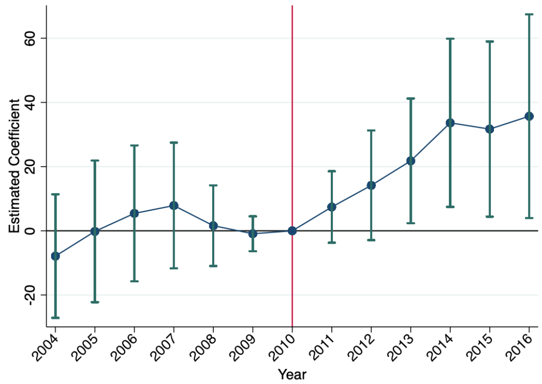
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2009) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Figures (a) and (b) report results for allegations. Figures (c), (d), (e), and (f) report results for false negatives. Figures (a), (c), and (e) are based on state-level analyses, whereas Figures (b), (d), and (f) are based on county-level analyses. Regressions are weighted by child population.

Table A18: Difference-in-Differences Results for 2009 Normalized

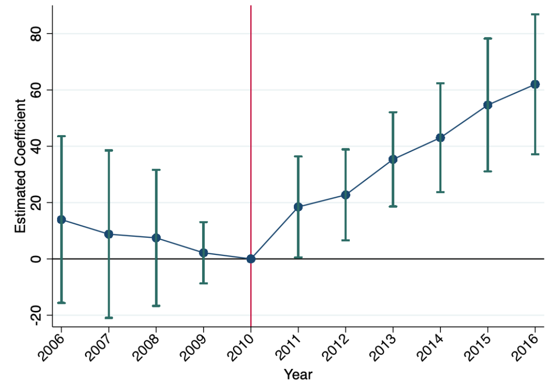
	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
Pre-reformulation	2.77	5.66	0.28	0.53	0.57	1.03
	(7.92)	(10.04)	(0.59)	(0.85)	(0.77)	(1.67)
Short-run	10.15**	15.27***	1.11**	1.04*	1.73	1.74
	(4.42)	(4.20)	(0.48)	(0.61)	(1.22)	(1.37)
	[4.1%]	[6.2%]	[7.6%]	[7.1%]	[2.8%]	[2.8%]
Medium-run	34.83**	47.31***	5.81***	6.10***	6.34**	6.55**
	(13.12)	(9.27)	(2.07)	(2.14)	(2.75)	(3.01)
	[14.2%]	[19.3%]	[39.7%]	[41.7%]	[10.2%]	[10.5%]
Mean	245.15	245.15	14.62	14.62	62.4	62.4
R-Squared	0.86	0.85	0.72	0.69	0.77	0.69
Observations	634	7073	506	4587	506	4587
State of County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5. Columns (1) and (2) report results for allegations. Columns (3), (4), (5), and (6) report results for false negatives. Columns (1), (3), and (5) are based on state-level analyses, whereas Columns (2), (4), and (6) are based on county-level analyses. Dependent variables in Columns (1), (2), (3) and (4) are measured per 10,000 children. Dependent variables in Columns (5) and (6) are measured 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 2009 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A21: Event Study Results for Allegations per 10,000 Children - Alternative Exposure



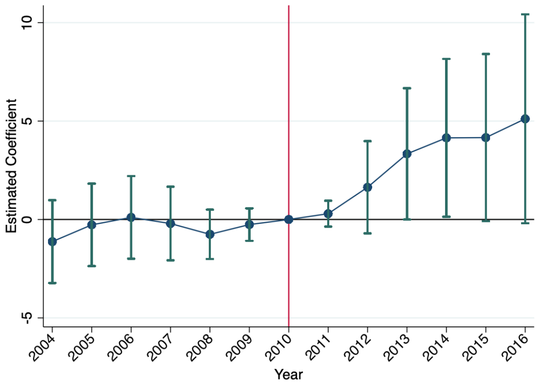
(a) Allegations by State



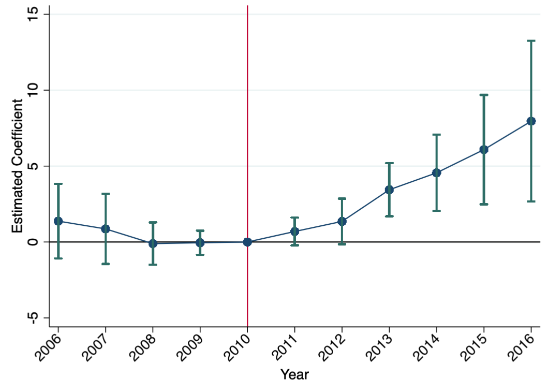
(b) Allegations by County

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 and Equation 3 that are adjusted for within-state clustering. State-level exposure measures are computed as the OxyContin misuse rate from 2004 to 2006. County-level exposure measures are computed as the Schedule II prescription opioids per capita from 2006 to 2007. The dependent variable is maltreatment allegations per 10,000 children. Figure (a) is based on a state-level analysis, whereas Figure (b) is based on a county-level analysis. Regressions are weighted by child population.

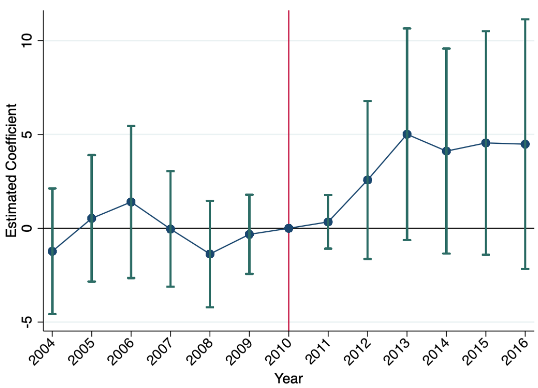
Figure A22: Event Study Results for False Negative Rates - Alternative Exposure



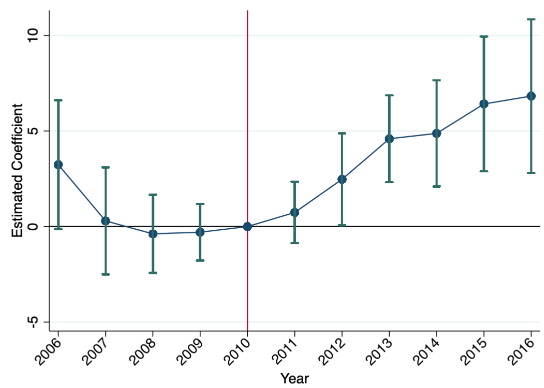
(a) FN by State, per 10K Children



(b) FN by County, per 10K Children



(c) FN by State, per 1K Allegations



(d) FN by County, per 1K Allegations

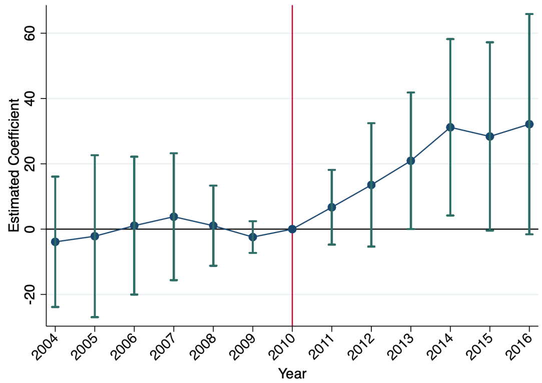
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 and Equation 3 that are adjusted for within-state clustering. State-level exposure measures are computed as the OxyContin misuse rate from 2004 to 2006. County-level exposure measures are computed as the Schedule II prescription opioids per capita from 2006 to 2007. The dependent variable is false negatives per 10,000 children and 1,000 allegations. Figure (a) is based on a state-level analysis, whereas Figure (b) is based on a county-level analysis. Regressions are weighted by child population.

Table A19: Difference-in-Differences Results for Alternative Exposures

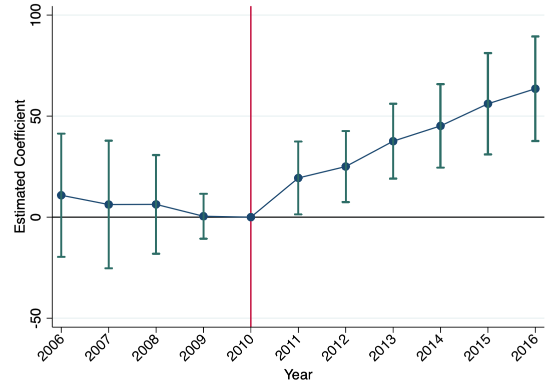
	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
Pre-reformulation	1.08	8.03	-0.43	0.49	-0.23	0.65
	(7.20)	(11.42)	(0.72)	(0.77)	(1.31)	(1.37)
Short-run	14.34**	25.47***	1.73*	1.81***	2.62	2.58**
	(7.12)	(7.99)	(0.97)	(0.53)	(1.71)	(1.08)
	[6.0%]	[10.6%]	[11.7%]	[12.2%]	[4.2%]	[4.2%]
Medium-run	33.30**	52.99***	4.39*	6.13***	4.27	5.96**
	(13.90)	(10.77)	(2.19)	(1.87)	(2.90)	(2.60)
	[13.9%]	[22.1%]	[29.7%]	[41.5%]	[6.9%]	[9.6%]
Mean	239.76	239.76	14.78	14.78	61.84	61.84
R-Squared	0.87	0.87	0.72	0.71	0.77	0.70
Observations	634	7073	506	4587	506	4587
State of County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5. Columns (1) and (2) report results for allegations. State-level exposure measures are computed as the OxyContin misuse rate from 2004 to 2006. County-level exposure measures are computed as the Schedule II prescription opioids per capita from 2006 to 2007. Columns (3), (4), (5), and (6) report results for false negatives. Columns (1), (3), and (5) are based on state-level analyses, whereas Columns (2), (4), and (6) are based on county-level analyses. Dependent variables in Columns (1), (2), (3) and (4) are measured per 10,000 children. Dependent variables in Columns (5) and (6) are measured 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

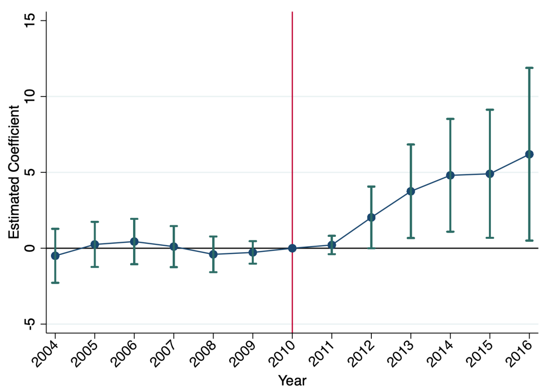
Figure A23: Event Study Results without Economic Covariates



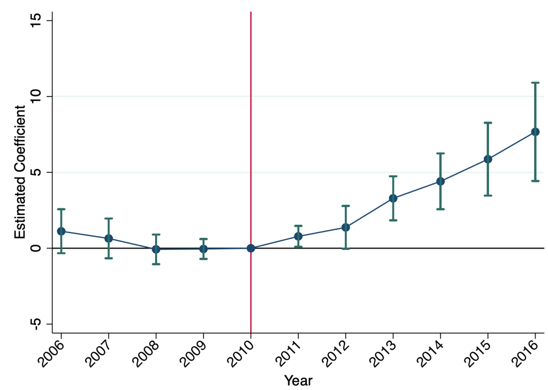
(a) Allegations by State



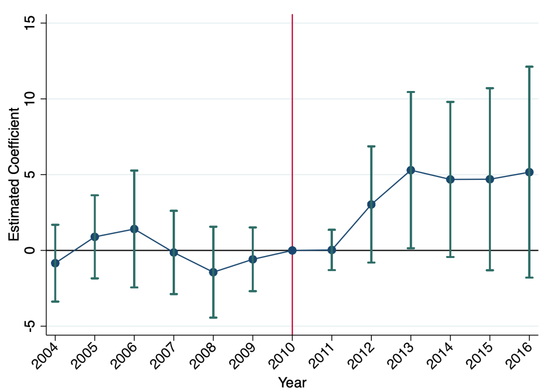
(b) Allegations by County



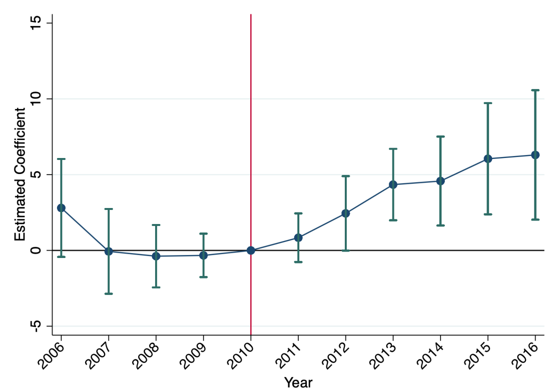
(c) FN by State, per 10K Children



(d) FN by County, per 10K Children



(e) FN by State, per 1K Allegations



(f) FN by County, per 1K Allegations

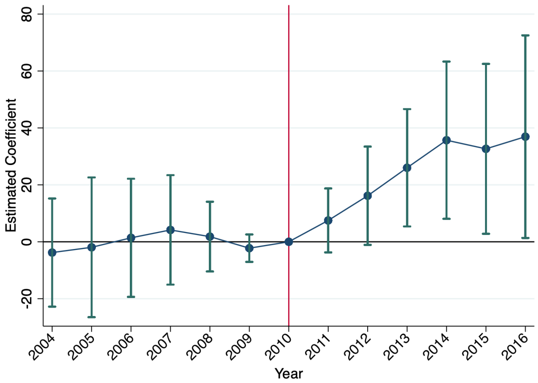
Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Figures (a) and (b) report results for allegations. Figures (c), (d), (e), and (f) report results for false negatives. Figures (a), (c), and (e) are based on state-level analyses, whereas Figures (b), (d), and (f) are based on county-level analyses. Unemployment rate and labor force participation rates were not included as controls. Regressions are weighted by child population.

Table A20: Difference-in-Differences Results without Economic Covariates

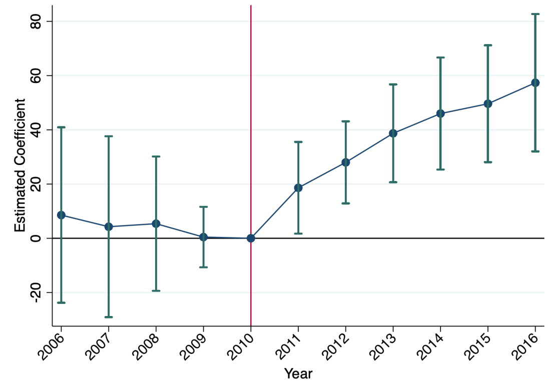
	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
Pre-reformulation	-0.30	5.95	-0.05	0.41	-0.12	0.50
	(7.57)	(11.90)	(0.54)	(0.75)	(1.25)	(1.37)
Short-run	13.60*	27.26***	1.97**	1.80***	2.76*	2.52**
	(7.83)	(8.50)	(0.86)	(0.56)	(1.55)	(1.13)
	[5.7%]	[11.4%]	[13.3%]	[12.2%]	[4.5%]	[4.1%]
Medium-run	30.36**	54.67***	5.23**	5.94***	4.77	5.59*
	(14.72)	(11.47)	(2.21)	(1.98)	(2.92)	(2.78)
	[12.7%]	[22.8%]	[35.4%]	[40.2%]	[7.7%]	[9.0%]
Mean	239.76	239.76	14.78	14.78	61.84	61.84
R-Squared	0.87	0.87	0.73	0.71	0.77	0.70
Observations	634	7073	506	4587	506	4587
State or County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5. Columns (1) and (2) report results for allegations. Columns (3), (4), (5), and (6) report results for false negatives. Figures (1), (3), and (5) are based on state-level analyses, whereas Columns (2), (4), and (6) are based on county-level analyses. Dependent variables in Columns (1), (2), (3) and (4) are measured per 10,000 children. Dependent variables in Columns (5) and (6) are measured per 1,000 allegations. Regressions are weighted by child population. Unemployment rate and labor force participation rates were not included as controls. Standard errors in parentheses are clustered at the state level. Percentage changes from the baseline mean in 2010 are reported in square brackets.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

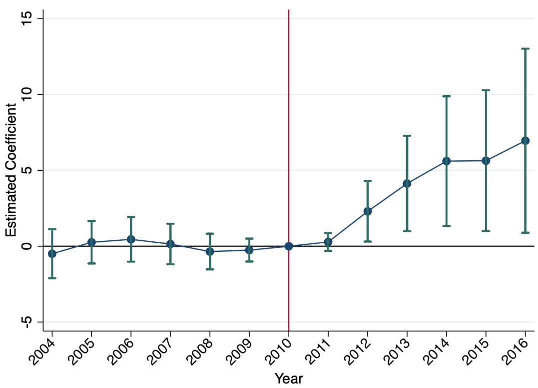
Figure A24: Event Study Results without Policy Covariates



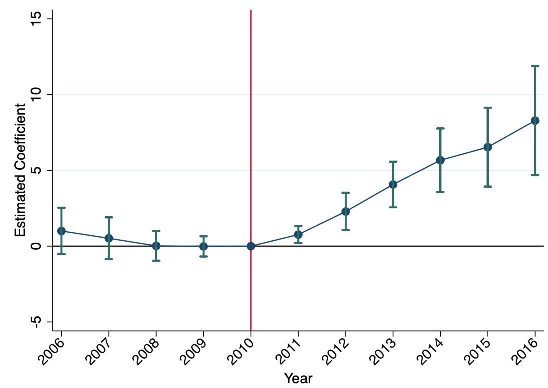
(a) Allegations by State



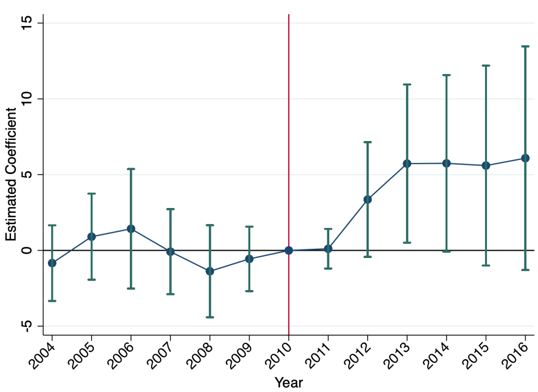
(b) Allegations by County



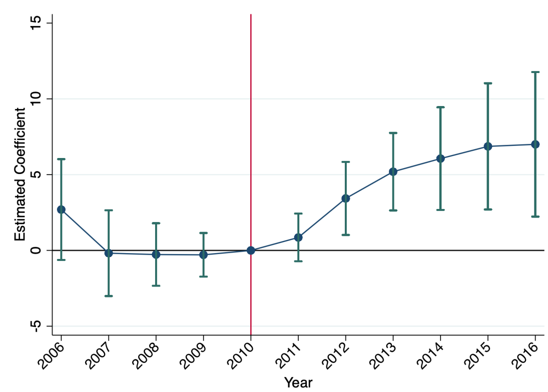
(c) FN by State, per 10K Children



(d) FN by County, per 10K Children



(e) FN by State, per 1K Allegations



(f) FN by County, per 1K Allegations

Notes. Each figure reports point estimates and 95 percent confidence intervals on δ_t (normalized to 0 in 2010) from Equation 2 and Equation 3 that are adjusted for within-state clustering. Figures (a) and (b) report results for allegations. Figures (c), (d), (e), and (f) report results for false negatives. Figures (a), (c), and (e) are based on state-level analyses, whereas Figures (b), (d), and (f) are based on county-level analyses. Policy variables as well as economic variables were not included as controls. Regressions are weighted by child population.

Table A21: Difference-in-Differences Results without Policy Covariates

	(1) Allegations Children State	(2) Allegations Children County	(3) FN Children State	(4) FN Children County	(5) FN Allegations State	(6) FN Allegations County
Pre-reformulation	0.06	4.66	-0.02	0.38	-0.08	0.47
	(7.40)	(12.42)	(0.53)	(0.78)	(1.28)	(1.43)
Short-run	16.47**	28.41***	2.22**	2.36***	3.06*	3.15**
	(7.56)	(8.11)	(0.87)	(0.72)	(1.56)	(1.37)
	[6.9%]	[11.8%]	[15.0%]	[16.0%]	[4.9%]	[5.1%]
Medium-run	34.94**	50.89***	6.05**	6.79***	5.80*	6.62*
	(15.35)	(11.05)	(2.46)	(2.49)	(3.25)	(3.44)
	[14.6%]	[21.2%]	[40.9%]	[45.9%]	[9.4%]	[10.7%]
Mean	239.76	239.76	14.78	14.78	61.84	61.84
R-Squared	0.87	0.87	0.73	0.71	0.77	0.70
Observations	634	7073	506	4587	506	4587
State or County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	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 4 and Equation 5. Columns (1) and (2) report results for allegations. Columns (3), (4), (5), and (6) report results for false negatives. Figures (1), (3), and (5) are based on state-level analyses, whereas Figures (2), (4), and (6) are based on county-level analyses. Policy variables as well as economic variables were not included as controls. 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.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$