The Hazards of Unwinding the Prescription Opioid Epidemic: Implications for Child Abuse and Neglect

Mary F. Evans[a], Matthew C. Harris[b], and Lawrence M. Kessler[b]

April 29, 2020

[a] Corresponding author: Robert Day School of Economics, Claremont McKenna College, Claremont, California; mevans@cmc.edu
[b] Department of Economics and Boyd Center for Business and Economic Research, University of Tennessee, Knoxville, Tennessee

Acknowledgements: We are grateful to Ethan Lieber, Justine Mallatt, Jessamyn Schaller, and Emily Lawler for their helpful comments. We also thank seminar participants from Claremont McKenna College, Williams College, University of Kentucky, University of Georgia, and University of Notre Dame; and conference participants at the International Health Economics Association.

Abstract:

We examine how two interventions designed to curtail prescription opioid misuse, the reformulation of OxyContin and the implementation of must-access prescription drug monitoring programs (PDMPs), affected child abuse and neglect. Our results suggest that counties with greater initial rates of prescription opioid usage experienced relatively larger increases in substantiated child abuse and neglect subsequent to OxyContin's reformulation. We also find larger increases in child abuse and neglect after must-access PDMP implementation in counties with higher pre-intervention exposure to opioids. Our results uncover unintended consequences of reducing the supply of an addictive good without adequate support (or alternatives) for dependent users.

1. Introduction

Consequences of the opioid epidemic are far-reaching, including effects on mortality (Case and Deaton, 2015; Dart et al., 2015; Alpert et al., 2018; Evans et al., 2019), morbidity (Powell et al., 2018), labor markets (Harris et al., 2019; Aliprantis et al., 2019; Hollingsworth et al., 2017), and birth outcomes (Patrick et al., 2012; Nelson et al., 2015; Chou et al., 2015). In recognition of these consequences, firms and policy makers have undertaken several interventions to reduce prescription opioid misuse through altering its supply. For example, states have adopted prescription drug monitoring programs (PDMPs) to track patient prescription histories, and pharmaceutical firms have introduced abuse deterrent formulas with physical properties that discourage abuse.

Despite significant coverage of the opioid epidemic, empirical knowledge of how the epidemic and the steps taken to alleviate the crisis have affected families is still relatively limited (Quast, 2018; Gihleb et al.,2019). In this paper, we examine the extent to which supply-side measures to curb the opioid epidemic have impacted child abuse and neglect. Child abuse and neglect has a profoundly large economic impact in the U.S., with estimates of the total economic burden ranging from $500 billion to $2 trillion per year (Fang, 2012; Peterson et al., 2018). We find that the implementation of these supply-side measures leads to an increase in child abuse and neglect in areas with higher pre-implementation levels of prescription opioid use.

The path by which a supply-side prescription opioid intervention might increase child abuse and neglect for some families is not immediately obvious. After all, the intervention is designed to reduce the misuse of prescription drugs by making it more difficult to access or abuse the drugs. However, efforts to restrict the supply of prescription opioids have heterogeneous effects on users and their families with some users/families benefitting and others suffering increased harm. Patterns of substitution likely reflect the extent to which an individual is dependent at the time supply is restricted. Less dependent users of prescription opioids may reduce or discontinue their opioid consumption altogether while those who are more heavily dependent may substitute towards more dangerous substances, such as heroin or black-market fentanyl (Evans et al., 2018; Mallatt, 2018).[1] Substitution towards more dangerous, illicit substances may increase the risk of child abuse and neglect and/or the propensity of others to report suspected abuse and neglect.

We consider two supply-side interventions, the reformulation of OxyContin and the implementation of must-access prescription drug management programs (PDMPs). In 2010, Purdue Pharma reformulated OxyContin, one of the most widely misused prescription medications, to make it more difficult to abuse. By 2017, all fifty states had operational PDMPs. Further, many of these PDMPS include a must-access provision, which requires practitioners and/or pharmacists to check the PDMP database before prescribing/dispensing Schedule II controlled substances. Prior work suggests that the implementation of must-access PDMPs reduces the misuse of Schedule II opioids (Buchmueller and Carey, 2018). However, Mallatt (2018) also finds that PDMPs lead to an increase in heroin-related crime in counties where opioid usage was more prevalent prior to implementation. Compared to PDMP implementation, the unintended, adverse effects of OxyContin's reformulation are generally worse and include an increase in heroin-related deaths (Alpert et al.,2018; Evans et al., 2019) and hepatitis C infections (Powell et al., 2018).

In our analysis of OxyContin's reformulation, we follow Evans et al. (2018) and Alpert et al. (2018) and consider two distinct periods – before and after the drug's 2010 reformulation. We adopt specifications that allow the effects of reformulation to vary across counties with different levels of exposure to prescription opioids prior to reformulation, similar to Alpert et al. (2018).[2] We also explore the extent to which the availability of therapeutic substitutes, specifically medical marijuana and buprenorphine, mediates the effects of OxyContin's reformulation. While buprenorphine has a specific therapeutic purpose to treat opioid dependence and withdrawal through medication assisted treatment (MAT), legal marijuana has also been found to reduce opioid addiction and overdose deaths (Powell et al., 2018; Garin et al., 2018). When we split the sample based on medical marijuana access, we find that the adverse effects of OxyContin's reformulation on child abuse and neglect are concentrated in

[1] For example, Pollini et al. (2011) found that "problematic" prescription opioid use was a precursor to heroin use among a high percentage of heroin users in San Diego, California.
[2] Alpert et al.'s (2018) analysis uses state-level data.

counties *without* medical marijuana. When we split the sample based on access to buprenorphine, the coefficients are estimated imprecisely but are suggestive of a similar phenomenon.[3] Therefore, while increased marijuana (or buprenorphine) usage may have some adverse effects (Solowij and Battisti, 2008; Soyka 2017), our results are consistent with increased access to these alternatives serving as a useful stopgap while attempting to decrease opioid dependence.

For our must-access PDMP analysis, we follow Buchmueller and Carey (2018), among others, and estimate difference-in-differences specifications.[4] We find relatively larger increases in child abuse and neglect after must-access PDMP implementation in counties with higher pre-intervention exposure.

The closest study to ours in the literature is a state-level analysis by Gihleb et al. (2019), which examines the effect of must-access PDMPs on engagement with the foster care system. Their results suggest that, after a delay of two years, must-access PDMP's reduce entry into the foster care. The contrast in results is attributable to several features of the data and research design, which we discuss in section 4.4. While foster care is worth examining in its own right, it is only part of the child welfare picture. In 2017, child protective service organizations received over four million referrals involving more than seven million children, whereas approximately 270,000 children entered foster care that same year (U.S. Department of Health and Human Services, 2019; Child Welfare Information Gateway, 2019). The path from a child abuse or neglect allegation to a foster care placement is a long and uncertain one, suggesting that foster care engagement captures only a small share of child abuse and neglect.

Our results indicate that supply-side measures taken to curtail the opioid epidemic are adversely affecting some children. The optimal unwinding of the opioid epidemic will require more than restricting access. Without adequate support, measures that simply restrict access can lead to adverse consequences for some dependent individuals and their families. While we cannot pinpoint the specific mechanisms that underlie our results, our findings are most

[3] These patterns are consistent with results from Doleac and Mukherjee (2019) who found that naloxone access increased emergency department visits and opioid related crimes – but that those effects were primarily found in areas with few treatment options for dependency.
[4] Similar difference-in-differences strategies were also used by Mallatt (2018); Nguyen et al. (2019) and Sacks et al. (2019).

consistent with the interventions pushing relatively high functioning dependents towards heroin and other substances more harmful than prescription opioids. In addition to evidence from the economics literature documenting substitution from prescription opioids to heroin, the clinical literature finds that while prescription opioids are conducive to maintaining a long-term habit, heroin is not. Individuals who have transitioned from prescription opioids to heroin report that heroin addiction is much worse, as is the suddenness and ferocity of withdrawal (Monico and Mitchell, 2018). Additionally, our results regarding the beneficial effects of marijuana and access to MAT are consistent with lessening substitution to heroin or polysubstance use (Gonzalez et al., 2004; Powell et al., 2018; Garin et al., 2018). Overall, our results suggest that simply shutting off the proverbial taps will likely generate negative externalities but public policies that increase access to favorable substitutes may lessen those impacts.

2. Background

2.1. Child abuse and neglect

The definition of child abuse and neglect varies across states, but generally refers to any acts or failures to act on the part of a parent or caregiver that result in harm or potential for harm to a child (Leeb et al., 2008). Most states recognize four types of abuse and neglect: neglect, physical abuse, psychological maltreatment, and sexual abuse (U.S. Department of Health and Human Services, 2019). In 2017, local child protective services (CPS) agencies received more than 4.1 million reports of possible child abuse and neglect involving 3.5 million children. Investigations concluded that approximately 674,000 children were victims of substantiated abuse or neglect, which corresponds to a national rate of 9.1 victims per 1,000 children. A supermajority of substantiated cases relate to neglect (74.9 percent). Most of the remaining cases involve physical abuse (18.3 percent of all substantiations). Approximately 8.6 percent of all cases involve sexual abuse, and 7.1 percent were victims of "other" types of abuse or neglect, including threats, drug/alcohol addiction, or lack of supervision (U.S. Department of Health and Human Services, 2019).[5,6]

Child abuse and neglect imposes significant private and social costs in the U.S. A myriad of adverse outcomes are associated with child abuse and neglect including lower academic achievement, psychological and behavioral problems, lower levels of employment and adult earnings, and increased risk of substance abuse (Eckenrode et al. 1993; Lansford et al., 2002; Currie and Widom, 2010; Cicchetti and Handley, 2019). In addition, state and local CPS agencies incur costs associated with investigations and the provision of services such as counseling, daycare, and foster care to help support child welfare. In total, state and local CPS agencies spent $29.9 billion in 2016 (Rosinsky and Williams, 2018). Estimates of the comprehensive economic impact of child abuse and neglect range from $500 billion to $2 trillion (Fang, 2012; Peterson et al., 2018).

2.2. The rise and reformulation of OxyContin

From 1991 to 2010, the number of opioid prescriptions written and dispensed in the U.S. increased from 76 million to over 250 million (Volkow, 2014).[7] While there are numerous causes and consequences of this increase, the most important aspect for our context is that prescribing in the 1990s and 2000s created a population of prescription opioid-dependent users vulnerable to disruptions in the supply of prescription opioids. Three features of the prescription opioid epidemic make this clear. First, with the release of OxyContin, Purdue Pharma sought to affect changes in prescribing practices. Purdue's marketing campaign targeted primary care providers to treat non-cancer chronic pain (Alpert et al., 2019; Tompkins et al., 2017; Quinones, 2015). Purdue also funded thought leadership to advocate for looser prescribing of pain medicine through the American Pain Society, which affected recommendations from Veterans Health, the Joint Commission on the Accreditation of

[5] These percentages exceed 100% as some victims may have suffered more than one type of child abuse or neglect.
[6] Types of child abuse and neglect that fall into this "other" category vary greatly from state to state.
[7] Data on 2010 prescription rates were retrieved from https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html on March 22, 2019.

Healthcare Organizations and others.[8] A working paper by Alpert et al. (2019), shows that not only did Purdue's efforts expose a large number of heretofore non-users to OxyContin, but their efforts to change prescribing culture increased prescribing for most Schedule II and III opioids.

Second, OxyContin, a major catalyst of the opioid epidemic, had two features that made it a singularly strong candidate for abuse. OxyContin was designed as a 'time-release' formulation – meaning that it contained multiple doses in a single pill. However, the time release feature was due to the physical properties of the pill; if the pill were crushed or dissolved, then those multiple doses could be experienced all at once (Van Zee, 2009). Additionally, Oxycodone, the narcotic ingredient in OxyContin, had until that point only been distributed in combination with acetaminophen. Acetaminophen, in large doses, has adverse effects on the liver and can induce liver failure. OxyContin, by contrast, was pure Oxycodone, uninhibited by acetaminophen, thereby removing a pharmacological governor's switch to prevent abuse (Cicero, 2013).[9]

Third, because it was designed for the treatment of chronic pain, OxyContin was purpose-built for long-term sustainable use. Kaiser Health News published documents from Purdue Pharma showing that in their promotions, they dubbed OxyContin "The Opioid to start with and stay with."[10,11] Together, these three factors created a large number of prescription opioid-dependent individuals at risk of substitution to more harmful substances once access became more difficult.

To curb the abuse of OxyContin, Purdue Pharma developed an abuse deterrent formula (ADF) of the drug, which was more difficult to crush or dissolve and take via non-oral routes.

---

[8] In the late 90's, the American Pain Society initiated a prominent campaign to treat pain as a "fifth vital sign" This initiative was adopted by the Veterans Health Administration in 1999 (Tompkins et al., 2017).[8] Shortly thereafter, the Joint Commission on the Accreditation of Healthcare Organizations (JCAHO) introduced pain scales and mandated pain management standards with regards to pain assessment and management for all accredited health care organizations in order to receive federal funding (Phillips, 2000; Ahmedani et al., 2014). These changes coincided with reduced oversight by the Federation of State Medical Boards and the Drug Enforcement Agency (DEA) with regards to the examination of opioid prescribing practices (Tompkins et al., 2017).

[9] These 'governor's' switches are not uncommon. Diphenoxylate, commonly used to treat diarrhea, is combined with Atropine (nightshade) to prevent individuals from abusing it.

[10] https://khn.org/news/how-america-got-hooked-on-a-deadly-drug/

[11] https://khn.org/news/purdue-and-the-oxycontin-files/

The Food and Drug Administration (FDA) approved this reformulated version in April 2010.[12] Purdue Pharma concurrently began shipping the new formulation while ceasing shipment of the old formulation in August 2010. The reformulation had its desired immediate effect , as opioid abuse, particularly of OxyContin, decreased sharply (Butler et al., 2013; Cicero and Ellis, 2015; Coplan et al., 2016; Havens et al., 2014; Severtson et al., 2013; Larochelle et al., 2015; Sessler et al., 2014). In fact, total opioid prescriptions leveled off between 2010 and 2012 and have decreased every year since (Guy Jr, 2017). Despite this decrease, opioid-related overdose deaths continued to rise throughout the most recent decade. In 2017, there were 47,600 opioid-related overdose deaths in the U.S., making it the leading cause of accidental deaths in the nation (Scholl et al., 2019).

2.3. Must-access PDMP laws

A second factor that impacted prescription opioid use was increased state-level enactment and stringency of PDMPs, the state-level databases that record prescriptions of controlled substances in order to monitor provider- and/or patient-specific prescription histories. States began enacting and implementing PDMPs in the early 2000s. Most PDMPs were initially optional and did not mandate any specific actions on the part of prescribers, a pattern that persisted for much of the 2000s.

In 2007, Nevada became the first state to include in its PDMP a "must-access" provision, which required providers to not only report all prescriptions, but also consult the PDMP to understand the patient's history *before* writing a prescription for a controlled substance. Louisiana and Oklahoma enacted must-access provisions in 2008 and 2011, respectively. A wave of other states followed suit starting around 2012. By 2017, all 50 states had enacted some sort of PDMP, although only 26 included a must-access provision.[13]

2.4. Reduced access to prescription opioids and potential for child abuse and neglect

Parental drug abuse is a major risk factor associated with child abuse and neglect (Kelley, 2002; Stith et al., 2009). In 2017, over 30 percent of child abuse and neglect victims

---

[12] Following Purdue Pharma, several pharmaceutical companies developed ADF versions of other prescription opioids. See https://www.fda.gov/drugs/postmarket-drug-safety-information-patients-and-providers/abuse-deterrent-opioid-analgesics.

[13] See Table A3 for a list of must access PDMP enactment dates by state through 2016.

involved a caregiver with drug abuse as a risk factor (U.S. Department of Health and Human Services, 2019). Prior to the opioid epidemic, previous research documented a causal relationship between methamphetamine use and child removals (Cunningham and Finlay, 2013) and an associative relationship between crack cocaine and child abuse and neglect (Kelley, 1992; Jaudes et al., 1995). More recently, testimony by child welfare professionals suggests that the misuse of opioids, including heroin, have put an enormous strain on the child welfare system, noting that prenatal opioid use can lead to neonatal abstinence syndrome (NAS), resulting in newborns being placed in protective custody, while post-natal opioid use can affect the parents' ability to safely care for their children (Young, 2016).[14]

Recent public health research explores child welfare outcomes during the opioid epidemic. Quast et al. (2018) find that higher prescription opioid rates in Florida are associated with substantial increases in child removals due to parental neglect. Lynch et al. (2018) document a considerable increase in the number of infants with NAS who were reported to child welfare services between 2004 and 2014. Finally, Bullinger and Wing (2019) estimate that from 2002 to 2017, the number of children living with an adult with opioid use disorder (OUD) grew by 30 percent, and the number of children living with an adult who uses heroin increased by 200 percent.

To understand how restricting access to prescription opioids can affect child abuse and neglect, consider a continuum of opioid dependence, with individuals distributed over that interval. While individuals near the lower end of the distribution may respond to reduced access with reduced usage of opioids, individuals in the higher percentiles of dependence are more likely to substitute to other drugs with similar pharmacological properties, such as heroin and fentanyl (Cicero and Ellis, 2015; Coplan et al., 2013; Compton et al., 2016).[15,16] The clinical literature documents the transition from prescription opioids to heroin and provides a strong argument for linking substitution to heroin to child abuse and neglect (Monico and Mitchell,

---

[14] Ghileb et al. (2020) find that PDMP adoption reduced the incidence of NAS.

[15] Morphine and heroin are both derived directly from the opium poppy, while oxycodone is derived indirectly through chemicals sourced from the opium poppy.

[16] Alpert et al. (2018) and Evans et al. (2018) show a causal linkage between the drug's reformulation and a rise in heroin overdose deaths. As a result, while deaths attributed to *prescription* opioids fell in direct response to OxyContin's reformulation, heroin overdoses actually rose.

2018). In a study of heroin users who transitioned from OxyContin and Schedule II opioids, participants on average used opioids for nine years before transitioning to heroin, but were in treatment within two years of first using heroin. All users reported some version of “life began unraveling at a much faster pace after I started using heroin.” Users reported that while withdrawal from OxyContin took more than a day to manifest, heroin withdrawal (including explosive diarrhea, vomiting, and pain) began within hours of non-usage and was an order of magnitude more severe than withdrawal from OxyContin. Intravenous heroin use led to even more dreadful and immediate withdrawal than nasal ingestion. Additionally, while heroin appeared much cheaper than prescription opioids on the surface, heterogeneity in purity/dosage, and the short acting nature of the drug meant that addicts spent more time and money seeking/procuring drugs after the switch to heroin (Monico and Mitchell, 2018).

In general, Romanowicz et al. (2019) note that direct observation studies find that “mothers with opioid use disorder, in comparison to controls, are more irritable, ambivalent, and disinterested while exhibiting greater difficulty in interpreting their children’s cues” (p. 9). Insofar as heroin usage decreases parent functionality, increases intensity of withdrawal, and is more all-consuming than Schedule II opioid use; parents who transition from prescription opioids to heroin face an increased risk of child abuse and neglect. It is therefore plausible that while restricting access to prescription opioids reduced opioid use at the population level, these restrictions also induced adverse substitution patterns among a subset of opioid users, leading to increased child abuse and neglect.

3. Data and preliminary evidence

We form child abuse and neglect outcomes for our analysis using data from NCANDS, which reflect reports of child abuse and neglect submitted to state CPS agencies. These data were obtained through a restricted data agreement with the National Data Archive on Child Abuse and Neglect (NDACAN). For a given year, the NCANDS data represent a census of CPS investigations and assessments that received a disposition (i.e., determination) in the federal fiscal year. State reporting under NCANDS is voluntary but most states and the District of

Columbia consistently report during the ten-year period covered by our analysis.[17] The NCANDS Child Files contain case-level information, where a case denotes a report-child pair. We use NCANDS Child Files for fiscal years 2006-2017.[18] Because our analysis is at the county-level, we aggregate the case-level data to obtain annual county-level measures of child abuse and neglect.[19]

Before aggregating, we combine the NCANDS Child Files for fiscal years 2006-2017. For cases (i.e. child-report pairs) that appear in multiple Child Files[20], we follow the recommendation in the NCANDS User's Guides to keep only the instance in the most recent fiscal year. For each case, we then identify the calendar year in which the suspected case was reported to the state CPS agency (as opposed to the fiscal year in which the case received a disposition). About 98 percent of cases receive a disposition within two years of being reported (e.g., a abuse/neglect report submitted in 2006 is almost certain to appear in the 2006 or 2007 Child File). Thus, combining the Child Files for 2006 through 2017 covers almost all reports of neglect or abuse received between 2006 and 2016.

A disadvantage of the NCANDS data for the empirical strategy we implement is that county identifiers are masked for a significant fraction of cases; NCANDS only reports county information for cases coming from counties with at least 1,000 total cases in the fiscal year.[21]

---

[17] This is not true of MD, MI, ND, and OR, each of which failed to report in at least one year between 2006 and 2017.

[18] The NCANDS Child Files (FFY2006v5, FFY2007v6, FFY2008v5, FFY2009v6, FFY2010v5, FFY2011v5, FFY2012v4, FFY2013v3, FFY2014v3, FFY2015v3, FFY2016v1, FFY2017v1) were provided by the National Data Archive on Child Abuse and Neglect (NDACAN) at Cornell University, and have been used with permission. The data were originally collected under the auspices of the Children's Bureau. Funding was provided by the Children's Bureau, Administration on Children, Youth and Families, Administration for Children and Families, U.S. Department of Health and Human Services. The collector of the original data, the funding agency, NDACAN, Cornell University, and the agents or employees of these institutions bear no responsibility for the analyses and interpretations presented here. The information and opinions expressed in this paper reflect solely the opinions of the authors.

[19] In the NCANDS data, county reflects the county of report or the jurisdiction to which the child report was assigned. Most states have a county-based system for investigating child abuse and neglect allegations so, for most cases the county of report is highly likely to be the county of residence. RI and MA represent exceptions. In RI, all cases are handled by the state-level office in Providence. As a result, no counties from RI will be included in our balanced panel. In MA, catchment areas for the Department of Social Services are not based on county boundaries; for cases in MA, the assigned county reflects the county associated with the area office responsible for investigating the case. Thus, while there are 14 counties in MA, all child abuse/neglect cases in MA are assigned to one of 11 counties.

[20] This can arise, for example, in the case of an appeal.

[21] Although our county-level analysis does not compromise confidentiality, efforts to obtain county-by-year data representing all counties from NDACAN were unsuccessful. While previous studies use county-by-year data (e.g.,

For cases from counties with fewer than 1,000 total cases, county is masked.[22] Given this limitation, we construct a balanced panel of counties reflecting counties that appeared in every Child File from 2006 to 2017. Our sample reflects 438 unique counties in 43 states and the District of Columbia from 2006 to 2016.[23] On average, counties included in our sample are less rural, younger, more Black, Hispanic, and female, with higher labor market participation and lower cancer rates (See Appendix Table A1). Figure 1 provides a map showing counties represented in the sample. Counties shaded in grey are excluded from our sample. While this data limitation affects the extent to which we can generalize our results to every county, over 60% of the U.S. population resides in the counties represented in our sample.[24] We also explore the sensitivity of our results to the inclusion of counties that are not represented in our balanced panel. Most of the excluded counties do not meet the NCANDS reporting threshold for the years covered in our sample period. While we cannot observe the extent of child abuse or neglect in each of these counties individually, we can use information on the state-level reports to construct one residual "super county" for each state. The super county is an aggregate of all counties in the state not represented in the balanced panel. We provide more detail on the process used to construct the super counties in Appendix A.[25]

We focus on neglect and physical abuse, the two most common types of child maltreatment and those with the clearest links to parental substance abuse.[26] We form two primary abuse and neglect outcomes, both measured annually at the child-level: the number of children with at least one report of physical abuse or neglect in the year (*allegations*) and the number of children considered to be victims of physical abuse or neglect for at least one report

---

Orsi et al., 2018), NDACAN is currently unable to provide researcher access to these data (personal correspondence with Christopher Wildeman, Director of NDACAN, 12/19/18).

[22] County is also masked for cases in which the child died to protect confidentiality.

[23] The following states are not represented in our balanced panel: MD, MI, ND, OR, RI, VT, WY. VT and WY had no counties that met the NCANDS reporting threshold for all years. See footnotes 12 and 14 for explanations of why the other states are not represented.

[24] This statement is based on population from the U.S. Census Bureau as of 2006, the beginning of the period covered by our sample.

[25] DE and MA do not have a super county as all of the cases in these states are assigned to counties and therefore are already reflected in the balanced panel. Because the following states have no counties represented in the balanced panel, the super county will consist of the entire state: MD, MI, ND, OR, RI, VT, WY.

[26] Many previous studies of child abuse and neglect in the economics literature also focus on physical abuse and neglect (e.g., Bitler and Zavodny, 2002; Currie and Widom, 2010; Paxson and Waldfogel, 1999).

in the year (*substantiations*). Allegations reflect only those instances of physical abuse or neglect that have been reported to state CPS agencies. A child is considered to be a victim if an allegation is determined by investigation to be substantiated or indicated according to the definition under state law. We combine these measures with child population counts from the Census to create rates per 1000 children

Both of our measures proxy for the underlying outcome of interest, the true amount of physical abuse and neglect, which is unobserved. Given the extent of underreporting and the failure to substantiate valid allegations of child abuse and neglect (Waldfogel, 1998), our measures likely underestimate the true amount of child maltreatment (Lindo and Schaller, 2014). As shown in Figure 2, for the median county in our sample, allegations trend upward during the 11 years covered by our analysis, increasing from about 43 per 1000 children in 2006 to 49 per 1000 children in 2016. Median substantiations fall slightly during the early period of our sample, rise between 2011 and 2014 and then remain constant at about 8.9 per 1000 children through 2016. Figure 1 shows the geographic distribution of allegations between 2006 and 2016 for sample counties, specifically the median number of children with alleged physical abuse or neglect in the county. The shading reflects quantiles of the distribution.

We obtain information on prescription opioid use from the Centers for Disease Control (CDC). The CDC data represent an 85% sample of retail pharmacy providers but exclude hospitals. Figure 2 shows that median per capita opioid prescriptions in our sample counties rise until a peak in 2012 and fall thereafter. Alpert et al. (2018) and Evans et al. (2019) explore national trends in OxyContin abuse using different measures and find a peak in 2010 at the time the drug was reformulated, roughly two years earlier than the peak of median opioid prescriptions for the counties in our sample. Between 2010 and 2012, 18 states began operating PDMPs according to the dates developed by Horwitz et al. (2018), and. A wave of must-access PDMP implementation began in 2012 (Sacks et al., 2019). Thus, the data indicate a reduction in prescription opioid use subsequent to the two supply-side interventions we study. Finally, we collect county-level demographic data (age, race, ethnicity, and gender) from the U.S. Census Bureau, county labor force information from the Bureau of Labor Statistics, and a county health-related variable on the number of cancer deaths from the Centers for Disease Control (CDC).

4. Empirical strategy and results

The empirical methods we adopt exploit variation in pre-intervention exposure to prescription opioids. Specifically, we explore the heterogeneous effects of two different interventions, the reformulation of OxyContin and the implementation of a must-access PDMP, on child physical abuse and neglect in counties with high levels of pre-intervention prescription opioid exposure compared to counties with low levels of exposure. Because of important differences in these two interventions, we employ different empirical specifications. The reformulation of OxyContin occurred at a specific point in time and resulted from an unanticipated, autonomous decision on the part of Purdue Pharmaceutical. Thus, for the purposes of identification, this intervention represents an exogenous shock. To explore the causal impact of OxyContin's reformulation on child abuse and neglect, we estimate event study and trend-break specifications as in Alpert et al. (2018). In contrast to OxyContin's reformulation, the implementation of must-access PDMPs happened at different times in different states and resulted from states' enactment decisions as well as the actions taken by the state to operationalize the PDMP. While previous work finds no evidence of differential trends prior to PDMP implementation (Buchmueller and Carey, 2018; Gihleb et al., 2019), the intervention is fundamentally different from the reformulation of OxyContin. Following related work, we estimate difference-in-differences (DD) specifications for the PDMP analysis (Buchmueller and Carey, 2018; Mallat, 2018; Sacks et al., 2019; Nguyen et al., 2019). We also explore variation in the DD estimate for counties above and below the median level of pre-intervention opioid exposure.

For both interventions, we require a county-level measure of pre-intervention opioid exposure to align with our county-level child abuse and neglect measures. Prior state-level analysis by Alpert et al. (2018) measures pre-intervention exposure as the population-weighted rate of OxyContin misuse in the state from 2004 to 2009, the period just prior to OxyContin's reformulation. This measure is unavailable at the county level so we measure pre-intervention exposure as the population-weighted mean number of all Schedule II opioid prescriptions per capita in the county for the period 2006 to 2009 from the CDC data.[27] Compared to Alpert et al.'s measure, our county-level measure of pre-intervention exposure reflects all uses (i.e., prescribed use and misuse) of all Schedule II prescription opioids (i.e., not just OxyContin) and thus allows for more precise local variation in pre-intervention exposure to opioids as a category. This feature is advantageous for our PDMP analysis as PDMPs target prescribing more broadly across opioid compounds but may impose a cost on our OxyContin analysis. For both analyses, we explore robustness of our results to replacing the county-level pre-intervention exposure measure with Alpert et al.'s state-level measure of misuse.

Before discussing our empirical strategy in more detail, we briefly comment on differences between the counties in our sample with higher and lower pre-intervention exposure. Table 1 provides means for outcomes and covariates in the pre-intervention period for sample counties with per capita opioid prescriptions below (in the second column), and equal to or above (in the third column) the sample median of 0.825. We refer to the former counties as low-exposure counties and the latter as high-exposure counties. By definition, high-exposure counties have higher mean opioid prescriptions per capita than low-exposure counties; they are also located in states with relatively higher pre- intervention levels of OxyContin misuse based on Alpert et al.'s measure. Compared to low-exposure counties, high-exposure counties are more rural, older, whiter, less Hispanic, with higher cancer death rates and lower labor force participation in the pre-intervention period. Finally, high-exposure counties have more alleged physical abuse or neglect than low-exposure counties between 2006 and 2009 although we detect no statistically significant difference for substantiated physical abuse or neglect.

4.1. *OxyContin analysis*

[27] The fact that different states implemented PDMPs at different times complicates the definition of a pre-intervention period. We focus on the 2006-2009 period because it precedes must-access PDMP implementation for almost all states as well as OxyContin's reformulation in 2010. Our choice of a uniform pre-intervention period means that for counties in states that adopted relatively early, say in 2011, the 2006-2009 pre-intervention period will be closer to the implementation date than for counties in states that adopted later. Only two states, Nevada and Louisiana, adopted must-access PDMPs during the 2006-2009 period. Our results are qualitatively similar with the exclusion of these two states.

In this section we estimate the causal impact of OxyContin's reformulation on child abuse and neglect, exploiting variation in pre-intervention exposure to prescription opioids across counties. We begin by examining whether there were differential changes in OxyContin misuse after reformulation based on the pre-reformulation opioid prescribing environment of a county (i.e., pre-intervention exposure). If the reformulation had larger effects on total prescription opioid use in some areas, we may expect to see more dramatic treatment effects in these areas as well.[28] Figure 3 depicts the relationship between pre-intervention exposure in the county and the change in the rate of OxyContin misuse in the state between 2008 and 2012 for the 438 counties in our sample. To generate the figure, we divide counties into quartiles based on the population-weighted mean number of opioid prescriptions per capita between 2006 and 2009. Quartile 1 (4) includes the 110 counties with the lowest (highest) exposure. Compared to counties in the lowest two quartiles based on pre-intervention per capita opioid prescriptions, counties in the highest two quartiles experience on average larger reductions in the rate of OxyContin misuse between 2008 and 2012 as measured by Alpert et al.'s state-level measure. Overall, the reformulation had the greatest effect on reducing OxyContin misuse, and potentially creating adverse substitution patterns, in areas where pre-reformulation usage was most prevalent.

To examine the causal impact of OxyContin reformulation on child abuse and neglect we consider two primary specifications, an event study and a trend-break model. In the event study, we interact event year indicators with the measure of pre-intervention exposure using specifications that take the following form:

$$y_{ct} = \alpha_c + \gamma_t + \delta_t \times PreExp_c + \varepsilon_{ct} \qquad (1)$$

where y_{ct} denotes the number of children with at least one allegation of physical abuse or neglect in county *c* and year *t* per 1000 children (allegations) or the number of children with at least one substantiated report of physical abuse or neglect in the county-year per 1000 children (substantiations). $PreExp_c$ represents pre-intervention exposure to prescription opioids in county *c* as described above. County-fixed effects, α_c, control for time-invariant cross-sectional differences across counties that contribute to differences in physical abuse and neglect. Year

[28] For example, Alpert et al. (2018) find that states with higher initial levels of OxyContin misuse saw larger declines in misuse after the drug's reformulation, but also saw larger increases in heroin deaths.

fixed effects, γ_t, control for time-varying national shocks to child abuse and neglect. The coefficients of interest are the set of δ_t event year coefficients, which identify differences in physical abuse and neglect between counties with higher and lower pre-intervention exposure in year *t* compared to 2010, the year OxyContin was reformulated.

Figure 4 presents our event study results with Panel A depicting results for allegations of physical abuse and neglect and Panel B showing results for substantiations.[29] We report point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. For both allegations and substantiations, the estimated coefficients in the years prior to reformulation are statistically indistinguishable from zero, consistent with no trend differences between counties with higher and lower exposure to prescription opioids during the pre-intervention period. After the reformulation, the number of children per 1000 with alleged and substantiated cases of child physical abuse or neglect begins increasing in high-exposure counties relative to low-exposure counties. All of the post-intervention event study coefficients are positive, suggesting a relative increase in physical abuse and neglect following reformulation in counties with higher rates of pre-intervention exposure. The estimated event study coefficients rise in each subsequent year through 2016, consistent with an increase in the magnitude of this differential effect on child abuse and neglect.

Similar to the effects of OxyContin's reformulation on overdose deaths found in Alpert et al. (2018) and Evans et al. (2019), the effects on child abuse and neglect grow over time. While the event study graphs show that the immediate effects of the reformulation are not statistically significant, they clearly document the start of a divergent trend among the high-exposure counties. It is important to note that, compared to heroin deaths, child abuse and neglect may take more time to become visible in the data. Unlike deaths, which are usually quickly reported, child abuse and neglect is observed only when it is sufficiently pronounced to prompt someone to report to a CPS agency. Suspected abuse and neglect is reported most frequently by educational, legal and law enforcement, and medical personnel but also by family members, neighbors, and other individuals (Children's Bureau, 2016). To the extent that drug

[29] The general pattern of results is similar when we include county- and time-varying controls. See Figure A1.

abuse leads to child abuse and neglect, these events may not immediately come to the attention of professionals. Other potential reporters (e.g., family members) may be reluctant to report given the potential implications of a substantiated claim of child abuse or neglect (e.g., child removal, criminal charges).

We conduct several robustness checks, all of which are available in Appendix A. We re-estimate event studies with time-varying county controls (Figure A1). We also re-estimate the event studies using a sample that includes super-counties to address concerns about the non-randomness of our balanced panel (Figure A2). Results are relatively unchanged. We replicate the event studies using an alternative measure of pre-intervention exposure, state-level misuse of OxyContin in Figure A3 (Alpert et al. 2018). Because Alpert et al.'s measure captures misuse of OxyContin in the state during the pre-intervention period, it may more accurately reflect a county's true exposure to OxyContin if pre-intervention misuse in the county is similar to the average pre-intervention misuse of the state. Finally, as a falsification test, we examine whether the reformulation of OxyContin led to a relative increase in sexual abuse. While the pathways from spiraling dependency to physical abuse and neglect are supported by prior work in the clinical and economics literature, the connection to sexual abuse is far less clear. While relative increases in sexual abuse would raise concerns about whether the event study results were spurious, we find no evidence of increased sexual abuse, post-reformulation, in high exposure counties compared to low exposure counties (see Figure A4).

4.1.1 Trend-break analysis

Next we consider a trend-break specification that allows us to estimate the cumulative effects of OxyContin's reformulation on physical abuse and neglect through the fifth year following reformulation. The trend-break specification takes the following form:

$$y_{ct} = \alpha_c + \gamma_t + \delta_1[Post_t \times PreExp_c] + \delta_2[t \times PreExp_c] + \delta_3[Post_t \times (t - 2011) \times PreExp_c] + X'_{ct}\lambda + \varepsilon_{ct} \quad (2)$$

$Post_t$ is an indicator variable equal to one in the years following the reformulation (i.e., 2011 through 2016) and *t* is a linear time trend. As noted by Alpert et al. (2018), equation (2) controls for pre-existing trends (through δ_2) and allows for a level shift (through δ_1) and a trend break beginning in 2011 (through δ_3). X_{ct} denotes a vector of county- and time-varying covariates including the percent of the county population in six age groups (0-14, 15-19, 20-24, 35-44, 45-54, 54-64, 65+), percent female, percent White, percent Black, percent Hispanic, percent rural, unemployment rate, labor force participation rate, and number of cancer deaths per 100,000 people, as well as state- and time-varying policy indicators for a PDMP of any form and a medical marijuana law.[30]

Tables 2 and 3 report the results of estimating equation (2) for the two outcome variables, the number of children per 1000 with alleged or substantiated cases of physical abuse or neglect, respectively. In each table, Panel A reports the estimated coefficients on the three δ terms in (2) while Panel B gives the implied effects of the OxyContin reformulation through the fifth year post-intervention. In both tables, column (1) reports the results from a model with only county and year fixed effects while the results in column (2) reflect the addition of county- and time-varying controls and those in column (3) reflect the further addition of state- and time-varying policy controls. The estimated coefficients and implied effects are similar across columns (1) through (3), suggesting that the inclusion of different sets of controls does not markedly change our results.

For allegations and substantiations, we detect a statistically significant impact of reformulation on child abuse and neglect (Tables 2 and 3; row 3). The estimated trend break term (δ_3) is consistently positive and statistically significant. For allegations, because the estimated level shift term is negative, the implied effects in Panel B of Table 2 are not statistically different from zero. For substantiations, the implied effects reported in Table 3 Panel B are all positive, and those after the first year are statistically significant. The implied 5-year effect indicates that a one unit increase in per capita opioid prescriptions between 2006 and 2009 leads to more than three additional children per 1000 with at least one substantiated report of physical abuse or neglect in 2015. This estimate implies that a standard deviation increase in initial opioid prescriptions per capita is associated with an additional 1.24 children per 1000 with substantiated physical abuse or neglect, an increase of about 13% relative to the mean of 9.1.

[30] Information on PDMPs comes from Horwitz et al. (2018). Medical marijuana law data are taken from Alpert et al. (2018) and http://www.ncsl.org/research/health/state-medical-marijuana-laws.aspx.

Appendix B contains several robustness checks for these results. First, we verify that results are qualitatively similar to those in Tables 2 and 3 when including super counties (Table B1). Second, we replicate these results using Alpert et al.'s state-level misuse of OxyContin as our measure for pre-intervention exposure (Table B2). For both outcome measures, estimates of the trend break term remain positive and statistically significant with this alternative measure of pre-intervention exposure. Finally, we verify that estimates of δ_3 are not driven by a single state. To that end, we replicate the trend-break model 44 times, leaving out all of the counties in a single state each time. Figure B1 plots the resulting estimates of δ_3, which are all positive.

4.1.2 Heterogeneous effects and complementary Policies

In this section, we examine the effects of the OxyContin reformulation on physical abuse and neglect separately. While this exercise may shed light on the mechanisms that underlie our results, variation across states in how physical abuse and neglect are defined complicates interpretation of the results. To further explore patterns of substitution following reformulation, we also examine the extent to which the reformulation's effects on physical abuse and neglect are mediated by medical marijuana policies and access to buprenorphine. Specifically, we replicate the trend-break specification after splitting our sample on the basis of a state-level medical marijuana law as of 2010 or the presence of at least one buprenorphine provider in 2010. [31,32]

Figures 5 and 6 contain event studies for alleged and substantiated cases of physical abuse and neglect, respectively. From Figure 5, the reformulation led to immediate and continued increases in physical abuse in high-exposure counties relative to low-exposure

[31] We use data from the Medicare Part D Provider Summary, courtesy of ProPublica, to create a variable that indicates the presence of at least one buprenorphine prescriber in the county in 2010 and divide the sample along this dimension. Buprenorphine, methadone, and naltrexone are approved by the Food and Drug Administration to treat opioid use disorder (OUD). Broadly these therapies are referred to as medication-assisted treatment (MAT) and, combined with psychosocial support, represent the current standard of care for OUD (Volkow and Collins, 2017). If the availability of buprenorphine reduces the number of former OxyContin abusers that transition to heroin by facilitating treatment, then it may moderate the impacts of OxyContin's reformulation on child abuse and neglect.

[32] Powell et al. (2018) and Garín et al. (2018), among others, provide evidence of potential substitution between prescriptions opioids and medical marijuana. If the availability of legal medical marijuana halts or slows the progression towards heroin, then we should observe differential effects of OxyContin's reformulation in counties located in states with medical marijuana laws compared to other counties.

counties. This is consistent with substitution to substances with more severe and immediate withdrawal, putting parents at increased risk of physical abuse. By contrast, the results for neglect are more gradual, which could arise from instances of neglect accumulating over time until becoming sufficiently problematic to trigger a report.

Tables 4 and 5 report our split-sample trend-break results for medical marijuana and buprenorphine access, respectively. The estimated coefficients in the allegations models have mixed significance. As a result, we confine our discussion to the results from the substantiation models reported in the right half of each table.[33] The median and modal county in our balanced panel had at least one buprenorphine provider in 2010, but did not have legal medical marijuana by that time. In some sense, the counties without buprenorphine or with legal marijuana can be considered opposite ends of the spectrum of medically available substitutes. In counties with neither buprenorphine nor medical marijuana, individuals dependent on prescription opioids facing reduced access in the aftermath of the reformulation had virtually no legal substitutes.

The results depicted in Table 4 suggest that virtually all of the impact of OxyContin's reformulation on physical abuse and neglect occurs among counties without legal access to medical marijuana prior to 2010. The estimated δ coefficients reported in the final columns of Tables 2 and 3 (i.e., the full sample results) and Table 4, for the subsample of counties without access to medical marijuana, are very similar, largely because 85 percent of counties do not have legal marijuana at the time of the reformulation. While we cannot confirm a causal link, our results are consistent with substitution towards medical marijuana, when available, muting the adverse consequences of OxyContin's reformulation on child abuse and neglect.

In Table 5, the estimated δ_3 coefficients for both outcomes are larger when the sample is restricted to counties without buprenorphine access. However, the coefficients are estimated imprecisely due to the small number of counties without access.[34] While imprecise, the pattern depicted by the implied five-year effects is again consistent with access to a therapeutic

[33] The general pattern of results based on coefficient magnitudes is similar for allegations although the estimated effects are statistically indistinguishable from zero.
[34] The sample of counties without access to buprenorphine includes only 34 counties located in 13 states.

substitute moderating the adverse effects of OxyContin's reformulation on child abuse and neglect.

Together, the results in Tables 4 and 5 are consistent with the idea that restricting the supply of an addictive good has greater adverse unintended consequences in areas with less access to substitutes or support. However, it is worth repeating that in our sample, counties in states *with* medical marijuana or *without* a buprenorphine provider constitute the tails. Approximately 75% of counties in our sample have at least one buprenorphine provider but are not located in a state with medical marijuana access as of 2010.

4.2 PDMP analysis

In this section, we analyze the second intervention of interest, the implementation of must-access PDMPs. Must-access provisions require physicians and/or pharmacists to check the PDMP database and view the patient's prescribing history *before* writing/dispensing an opioid prescription. Examining the implementation of must-access provisions complements the OxyContin analysis because it speaks directly to the generalizability of our results. Broadly speaking, if multiple, distinct efforts to reduce prescription opioid abuse have adverse consequences for children, then potential spillovers in the form of child abuse and neglect need to be considered when designing interventions.

4.2.1 Differences-in-differences (DD) specification and results

We follow Mallatt (2018), Buchmueller and Carey (2018), Nguyen et al. (2019), and Sacks et al. (2019) and adopt a difference-in-differences (DD) approach to estimate the effects of must-access PDMPs on alleged and substantiated physical abuse and neglect. We use implementation dates provided by Sacks et al. (2019), which were sourced from the National Alliance for Model State Drug Laws (NAMSDL).[35] Because must-access PDMP's were implemented in different states in different years, we apply the Goodman-Bacon (2019) decomposition to examine how the variation in treatment timing and the time-varying composition of the "treatment" and "control" groups impact our results.[36] For examining the

[35] Appendix Table C1 lists the must-access PDMP implementation dates we use in our analysis.
[36] These results should be interpreted with some caution as states may have chosen to implement a must-access PDMP due to some unobserved factors that could be correlated with both opioid prescriptions and child abuse and neglect. We therefore do not suggest that these policies are strictly exogenous. Second, Horwitz et al. (2018)

effects of must-access PDMPs, our control group is a combination of states with no PDMP and states with a PDMP but no must-access provision as in Buchmueller and Carey (2018).[37]

We estimate a simple two-way fixed effects model of the form:

$$y_{cst} = \alpha_c + \gamma_t + \beta_1 PDMP_{st} + \beta_2 \boldsymbol{X}_{cst} + \varepsilon_{cst}$$

where y_{cst} denotes the number of children with physical abuse or neglect allegations (or substantiations) per 1,000 children in county c, state s, and year t; α_c and γ_t represent county and year fixed effects respectively; $PDMP_{st}$ is a dummy variable equal to one in the year that state *s* implements a must-access PDMP and every year thereafter (otherwise zero), and $\boldsymbol{X}_{cst}$ is a vector of additional control variables.

Figure 7 explores trends in alleged physical abuse or neglect (Panel A) and substantiated physical abuse or neglect (Panel B) during the period of must-access PDMP implementation. To produce these figures, we divide counties into two groups, those in states where a must-access PDMP is implemented before the end of our sample period, 2016, and those in states where a must-access PDMP is not implemented during our sample period. The vertical reference line in 2012 marks the start of the wave of must-access PDMP implementations. Prior to 2012, only three states had implemented must-access PDMPs. Five states implement in 2012 and for each of the years between 2013 and 2015, three additional states follow suit. The year 2012 therefore marks the start of the period where time-varying treatment begins in earnest, and in that year, the previously parallel lines for the ever-treated and never-treated counties begin to diverge.

Table 6 reports the DD results for the full sample as well as subsamples split based on the median level of pre-intervention exposure to prescription opioids. Results for the full sample indicate that following the implementation of a must access PDMP, the number of children per 1,000 with alleged physical abuse or neglect increases by roughly five while the number of children per 1,000 with substantiated physical abuse or neglect increases by

---

document inconsistencies in PDMP implementation dates across data sources, suggesting the potential for some degree of measurement error.

[37] Buchmueller and Carey (2018) find that the implementation of must-access PDMPs reduces measures of opioid misuse, but find no such effect among states with a PDMP that has no must-access provision. More specifically, they find little difference between the states with a PDMP that has no must-access provision and states without any PDMP altogether. They therefore group these two latter categories together into a single control group.

approximately one. The split-sample results indicate larger impacts on both alleged and substantiated physical abuse and neglect among counties above the median level of pre-intervention exposure to opioids compared to those below, by over 20%.[38]

4.2.2 Bacon decomposition

Due to the staggered timing of must-access PDMP implementation, the DD estimates represent a weighted average of all possible comparison pairs of DD estimators in the data (Goodman-Bacon, 2019). To determine which sources of variation drive our estimates, we perform a Bacon decomposition, the results of which are presented in Table 7. For each of the possible treatment-control comparisons, the Bacon decomposition produces an average DD estimate as well as a weight. The decomposition indicates that 87 percent of the weight of the DD estimates reported in Table 6 is from the comparison between the treated observations (i.e., those with a must-access PDMP) versus the never treated observations (i.e., those with no must-access PDMP provision or no PDMP altogether). Very little variation is sourced from the staggered timing of must-access PDMP implementation. Finding that such a large majority of the estimated treatment effect is *not* due to variation in timing further validates the pattern of pre-treatment trends depicted in Figure 7.

For completeness, the Goodman-Bacon decomposition also enables plots of the values of each treatment-control comparison pair (i.e., 2x2 DD estimates) for the three comparisons groups for each discrete point in time in which observations are treated.[39] Plots of estimated average effects (y-axis) and weights (x-axis) are shown in Figure 8. From the above, it follows that the majority of comparisons between observations treated at different points in time, depicted by dark and lighter shaded x's in the figure, are associated with small weights. We therefore focus on the magnitudes and weights from the treated verses never-treated comparisons (i.e., triangles in the figure). While not labeled, the largest weights are associated with the 2012, 2013, and 2014 2x2 estimates, which is consistent with the stylized observation

[38] In Appendix Table C2, we present results using Alpert et al.'s state-level measure of pre-intervention exposure. Results for substantiations are consistent with the central tendency of the results from Table 6 – that is, must-access PDMPs only lead to an increase in substantiated cases among counties in states that were above the median for OxyContin misuse. For allegations, however, results indicate that the marginal effects of PDMP's were larger in counties below the median.

[39] The three comparison groups, which are also listed in Table 7 are: earlier treated versus later control, later treated versus earlier control, and treated versus never treated.

in Figure 7 that the treatment and control groups exhibit increased divergence starting in 2012 and then decreased divergence after 2014.

4.2.3 Comparison to Gihleb et al. (2019)

A paper closely related to ours is Gihleb et al. (2019), which finds that the implementation of "mandatory access" PDMPs reduces admissions to the foster care system.[40] In contrast to our findings, their results imply that must-access PDMPs have positive spillover effects on children. Several factors contribute to our divergent findings. For example, Gihleb et al. compare states with a must-access PDMP to states with any operational PDMP so their sample excludes states without PDMPs.

In this section, we reconcile what we believe to be the most important difference between our study and Gihleb et al.'s: the assignment to treatment and control groups and the timing of treatment (i.e., dates on which states implemented their must-access PDMP). We use information from Sacks et al. (2019) to assign each state in each year to either the treatment group (i.e., states that have implemented must-access PDMPs) or to the control group (i.e., states that have not implemented must-access PDMPs). By comparison the information used in Gihleb et al. (2019) were gathered from a number of sources including the NAMSDL, but also Brandeis University's Prescription Monitoring Program Training and Technical Assistance Center, state legislative laws and bills, government newsletters, news articles, articles from peer reviewed journals, and pharmacy board websites.

A year-by-year comparison of the treatment and control groups for the two studies suggests a number of differences, the most important of which relates to Florida. According to Gihleb et al. (2019), Florida implemented a must-access PDMP in 2011. Conversely, in Sacks et al. (2019), Florida does not have a must-access PDMP whatsoever. Further examining Florida's statutes, we find that Florida did in fact change their PDMP laws in 2011, but did not adopt a must-access PDMP at that time, rather they adopted a less stringent mandatory reporting PDMP, which requires providers to report the dispensation of a controlled substance to the

[40] Gihleb et al. (2019) use the term "mandatory access" while we adopt the term "must-access" following Buchmueller and Carey (2018), and Sacks et al. (2019), among others. In our description of Gihleb et al.'s work, we use "must-access PDMP" to refer to their results about "mandatory access" PDMPs. These terms can be used interchangeable as they both refer to provisions which require the provider to check the PDMP database *before* writing/dispensing a prescription.

PDMP database *after* the fact.[41] This is substantively different than a must-access PDMP, which requires the prescriber/dispenser to consult the PDMP database to review a patient's prescription history *before* prescribing a controlled substance. Florida did not, in fact, switch to a must-access PDMP until 2018 when Governor Rick Scott signed HB21 into law. In the case of Florida, it seems that Gihleb et al. (2019) conflate mandatory reporting PDMPs with must-access PDMPs.

While we are confident in claiming that the Florida date used in Gihleb et al. (2019) does not reflect a must-access provision, different explanations may underlie other inconsistencies between the two studies.[42] Horwitz et al. (2018) document variation in PDMP implementation dates across data sources, suggesting the potential for some degree of measurement error in the implementation dates that we use and those used in Gihleb et al. (2019). Given this, we explore how the estimated effect of must-access PDMP implementation on child abuse and neglect varies with different assumptions about assignment to and timing of treatment. In the first column of Table 8, we present results from our DD specification with two baselines for treatment assignment and timing of treatment: Panel A uses information from Gihleb et al., Panel B uses the information we employ from Sacks et al. (2019).[43] Each subsequent column then 'flips' one state, replacing the baseline assumption on treatment status (or timing of treatment) for that state with the analogous assumption in the other study. In the case of Gihleb et al. (Panel A), we reassign a given state the treatment status (or timing of treatment) from our data, and vice versa. The two key takeaways from Table 8 are that results using the

[41] According to Florida's 2011 statute 893.055: "each time a controlled substance is dispensed to an individual, the controlled substance shall be reported to the department through the system as soon thereafter as possible, but not more than 7 days after the date the controlled substance is dispensed." https://www.flsenate.gov/Laws/Statutes/2011/0893.055. Accessed on February 19, 2020

[42] Like Florida, Texas and Mississippi are assigned to the control group in our analysis but treatment states in Gihleb et al.'s. Oklahoma, Georgia, and Indiana are considered treatment states (i.e., with must-access PDMPs) in our analysis but Gihleb et al. treat these states as control states (i.e., with PDMPs but no must-access provisions). Both analyses treat Ohio, Louisiana, and Massachusetts as treatment states but the timing of treatment is different between the two studies.

[43] For this exercise, we measure child maltreatment as the total number of allegations or substantiations (of any kind) because Florida is one of the few states where a large proportion of maltreatment cases are classified as "other" rather than as physical abuse or neglect. For example, in 2017, 44.8 percent of maltreatment cases in Florida were classified into the other category, while for the nation as a whole only 7.1 percent of cases were classified as "other" (U.S. Department of Health and Human Services, 2019). DD results with all allegations and all substantiations (first column of Table 8, Panel B) are similar to our main DD results, where we focus on alleged and substantiated physical abuse or neglect (first row of Table 6).

information from Sacks et al. are generally robust to changing one state, but Florida matters a lot.[44]

In the Gihleb et al. baseline, we find negative and insignificant results, qualitatively consistent with the findings from their paper. However, once Florida is appropriately removed from the treatment group, the sign of the DD estimates flip and the results suggest that must-access PDMPs are associated with a statistically significant *increase* in substantiated child maltreatment. By the same token, when you *incorrectly* add Florida to the treatment group in our sample, the relationship between must-access PDMP implementation and substantiated maltreatment becomes negative and insignificant.[45] Results using our baseline are not otherwise sensitive to assumptions about a single state. The extent to which Gihleb et al.'s results on foster care admissions are robust to alternative assumptions about treatment assignment or timing of treatment remains unclear but the results in Table 8 suggest that differences in assumptions regarding these features provide one explanation for the divergence in ours and Gihleb et al.'s findings.

5. Discussion

Aside from anecdotal evidence[46], there continues to be a dearth of systematic evidence on the causal impacts of the opioid epidemic on children. We explore the implications for child abuse and neglect of two supply-side interventions designed to reduce prescription opioid abuse—the reformulation of OxyContin and the implementation of must-access PDMPs. Studying both of these interventions is valuable because of the structural differences between the two. While PDMPs and abuse-deterrent prescription opioid formulas both represent examples of supply-side responses, the implementation of a typical PDMP happens gradually over time, often with years between the legislated start of a PDMP and when the PDMP

[44] In reviewing state statutes we were unable to confirm the must-access implementation dates for Georgia and Indiana used in Sacks et al. (2019) and our analysis. Therefore, in Column 8 of Table 8 we also "flip" both of these states simultaneously. We find that the relationship between must-access PDMP implementation and substantiated child maltreatment is robust to the inclusion or exclusion of these two states from the treatment group. This is not the case for alleged maltreatment.

[45] The DD estimate in the case of allegations remains positive but is almost half the size of the baseline DD estimate.

[46] See for example, Quinton (2015), Birnbaum and Lora (2018), and Stein and Bever (2017).

becomes fully operational (Horwitz et al., 2018). In contrast, the reformulation of OxyContin was unanticipated and only a few months passed between the FDA's approval of the reformulated version in April 2010 and the time at which Purdue Pharma stopped distributing the original version and started distributed the reformulated version in August 2010 (Alpert et al., 2018). The abrupt, unanticipated reformulation of OxyContin caused more substitution towards heroin in areas with greater access to heroin (Evans et al., 2019), consistent with previous heavy abusers of OxyContin seeking out the most readily-available substitute. The more gradual roll-out of PDMPs may have given heavy abusers of prescription opioids more flexibility in seeking out substitutes or reducing/discontinuing their opioid use.

Overall, our results identify an adverse effect on some children from both supply-side measures taken to unwind the opioid epidemic. If parents who are dependent on opioid prescriptions are cut off from supplies, even if they do not substitute immediately to heroin or fentanyl, they may suffer physical and emotional distress, which can create friction in the home. While we cannot identify the specific mechanism responsible for the linkage between changes in prescribing and child abuse and neglect, this finding is nevertheless important from a policy perspective. The optimal unwinding of the opioid epidemic will require more than restricting access, and support services could play a crucial role. Increasing the provision of medication-assisted treatment, such as buprenorphine, for individuals with opioid use disorder is one such support measure. The *Family First Prevention Services Act*, enacted in 2018, is a promising policy step in this respect as it gives states the option to use federal funds to help children at risk of entering foster care and their parents/caregivers by providing services such as substance use disorder treatment, mental health services, and in-home parenting skills training (Waite et al., 2018). Nonetheless, without adequate support for dependents and their families, measures that simply restrict access to prescription opioids risk adverse consequences.

The findings from this study are especially important for combating substance use disorder in the long run, as children who experience abuse and neglect are themselves at a greater risk of developing substance use disorders later in life (Cicchetti and Handley, 2019; Elliott et al., 2014; Huang et al., 2011; Tonmyr et al., 2010; Spatz Widom et al., 2006; White and Widom, 2008), and are more likely to abuse their own children (Buckingham and Daniolos, 2013). Thus, coarse short-run measures to reduce the supply of addictive goods may create subsequent addiction challenges in the future.

REFERENCES

Ahmedani, B. K., E. L. Peterson, K. E. Wells, D. E. Lanfear and L. K. Williams (2014). "Policies and events affecting prescription opioid use for non-cancer pain among an insured patient population." Pain physician 17(3): 205-216.

Alpert, A., D. Powell and R. L. Pacula (2018). "Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids." American Economic Journal: Economic Policy 10(4): 1-35.

Bartholow, M. (2011). "Top 200 Drugs of 2010." Retrieved March 2019, from https://www.pharmacytimes.com/publications/issue/2011/may2011/top-200-drugs-of-2010.

Birnbaum, E., and M. Lora. (2018). “Opioid crisis sending thousands of children into foster care.” The Hill. June 20. Accessed August, 20, 2018: https://thehill.com/policy/healthcare/393129-opioid-crisis-sending-thousands-of-children-into-foster-care

Bitler, M., and M. Zavodny (2002). “Child Abuse and Abortion Availability.” *American Economic Review* 92(2): 363-367.

Boudreau, D., Von Korff, M., Rutter, C.M., Saunders, K., Ray, G.T., Sullivan, M.D., Campbell, C.I., Merrill, J.O., Silverberg, M.J., Banta-Green, C. and Weisner, C. (2009). "Trends in long-term opioid therapy for chronic non-cancer pain." Pharmacoepidemiology and drug safety 18(12): 1166-1175.

Buchmueller, T. C., and C. Carey. (2018). “The effect of prescription drug monitoring programs on opioid utilization in Medicare.” *American Economic Journal: Economic Policy* 10(1): 77-112.

Buckingham, E. T. and P. Daniolos (2013). "Longitudinal Outcomes for Victims of Child Abuse." Current Psychiatry Reports **15**(2): 342.

Bullinger, L. R. and C. Wing (2019). "How many children live with adults with opioid use disorder?" Children and Youth Services Review, 104381.

Butler, S. F., T. A. Cassidy, H. Chilcoat, R. A. Black, C. Landau, S. H. Budman and P. M. Coplan (2013). "Abuse rates and routes of administration of reformulated extended-release oxycodone: initial findings from a sentinel surveillance sample of individuals assessed for substance abuse treatment." The Journal of Pain 14(4): 351-358.

Carise , D., K. Leggett Dugosh, A. T. McLellan, A. Camilleri , G. E. Woody and K. G. Lynch (2007). "Prescription OxyContin Abuse Among Patients Entering Addiction Treatment." American Journal of Psychiatry 164(11): 1750-1756.

Case, A., and A. Deaton. (2015). “Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century.” *Proceedings of the National Academy of Sciences* 112 (49): 15078–83.

Chaffin, M., K. Kelleher and J. Hollenberg (1996). "Onset of physical abuse and neglect: Psychiatric, substance abuse, and social risk factors from prospective community data." Child abuse & neglect 20(3): 191-203.

Children’s Bureau, U.S. Department of Health and Human Services. 2016. *Child Maltreatment 2016*. Accessed online on 3/17/19 at https://www.acf.hhs.gov/sites/default/files/cb/cm2016.pdf.

Child Welfare Information Gateway. (2019). Foster care statistics 2017. Washington, DC: U.S. Department of Health and Human Services, Children’s Bureau.

Chou, R., J. A. Turner, E. B. Devine, R. N. Hansen, S. D. Sullivan, I. Blazina, T. Dana, C. Bougatsos, and R. A. Deyo (2015). The e_ectiveness and risks of long-term opioid therapy for chronic pain: a systematic review for a national institutes of health pathways to prevention workshop. Annals of Internal Medicine 162 (4), 276-286.

Cicchetti, D. and E. D. Handley (2019). "Child maltreatment and the development of substance use and disorder." Neurobiology of Stress **10**: 100144.

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

Cicero, T. J., Ellis, M. S., Surratt, H. L., & Kurtz, S. P. (2013). Factors influencing the selection of hydrocodone and oxycodone as primary opioids in substance abusers seeking treatment in the United States. PAIN® 154(12): 2639-2648.

Cicero, T. J., J. A. Inciardi and A. Muñoz (2005). "Trends in Abuse of OxyContin® and Other Opioid Analgesics in the United States: 2002-2004." The Journal of Pain 6(10): 662-672.

Compton, W. M., C. M. Jones and G. T. Baldwin (2016). "Relationship between nonmedical prescription-opioid use and heroin use." New England Journal of Medicine 374(2): 154-163.

Connell, C. M., N. Bergeron, K. H. Katz, L. Saunders and J. K. Tebes (2007). "Re-referral to child protective services: The influence of child, family, and case characteristics on risk status." Child Abuse & Neglect 31(5): 573-588.

Coplan, P. M., H. D. Chilcoat, S. F. Butler, E. M. Sellers, A. Kadakia, V. Harikrishnan, J. D. Haddox and R. C. Dart (2016). "The effect of an abuse-deterrent opioid formulation (OxyContin) on opioid abuse-related outcomes in the postmarketing setting." Clinical Pharmacology & Therapeutics 100(3): 275-286.

Coplan, P. M., H. Kale, L. Sandstrom, C. Landau and H. D. Chilcoat (2013). "Changes in oxycodone and heroin exposures in the National Poison Data System after introduction of extended-release oxycodone with abuse-deterrent characteristics." Pharmacoepidemiology and drug safety 22(12): 1274-1282.

Cunningham, S. and K. Finlay (2013). "Parental substance use and foster care: Evidence from two methamphetamine supply shocks." Economic Inquiry 51(1): 764-782.

Currie, Janet, and Cathy Spatz Widom. "Long-term consequences of child abuse and neglect on adult economic well-being." *Child maltreatment* 15.2 (2010): 111-120.

Dart. R. C., H. L. Surratt, T. J. Cicero, M. W. Parrino, S. G. Severtson, B. Bucher-Bartelson, and J. L. Green. (2015). "Trends in Opioid Analgesic Abuse and Mortality in the United States." *New England Journal of Medicine* 372 (3): 241–48.

Eckenrode, John, Molly Laird, and John Doris. "School performance and disciplinary problems among abused and neglected children." *Developmental psychology* 29.1 (1993): 53.

Elliott, J. C., et al. (2014). "The risk for persistent adult alcohol and nicotine dependence: the role of childhood maltreatment." Addiction **109**(5): 842-850.

Evans, W. N., Lieber, E. M. J., Power, P. (2019). "How the reformulation of OxyContin ignited the heroin epidemic." The Review of Economics and Statistics 101(1): 1-15.

Fang, X., Brown, D. S., Florence, C. S., & Mercy, J. A. (2012). "The economic burden of child maltreatment in the United States and implications for prevention." Child Abuse & Neglect, 36(2), 156–165.

Friedman, M. S., et al. (2011). "A meta-analysis of disparities in childhood sexual abuse, parental physical abuse, and peer victimization among sexual minority and sexual nonminority individuals." American journal of public health **101**(8): 1481-1494.

Fuller, T. L. and S. J. Wells (2003). "Predicting Maltreatment Recurrence among CPS Cases with Alcohol and Other Drug Involvement." Children and Youth Services Review 25(7): 553-569.

Garín, Julio, R. Vincent Pohl, and Rhet A. Smith. 2018. “The effect of medical cannabis dispensaries on opioid and heroin overdose mortality.” Claremont McKenna College Robert Day School of Economics and Finance Research Paper No. 3270101.

Gihleb, R., O. Giuntella, and N. Zhang. (2019). “The effects of mandatory prescription drug monitoring programs on foster care admissions.” Journal of Human Resources, December 6, 2019 0918-9729R2.

Gihleb, R., O. Giuntella, and N. Zhang. (2020). “Prescription drug monitoring programs and neonatal outcomes.” Regional Science and Urban Economics 81, 103497.

Gonzalez, G., Oliveto, A., & Kosten, T. R. (2004). Combating opiate dependence: a comparison among the available pharmacological options. Expert Opinion on Pharmacotherapy, 5(4), 713-725.

Guy Jr, G. P., Kun Zhang, Michele K. Bohm, Jan Losby, Brian Lewis, Randall Young, Louise B. Murphy, and Deborah Dowel (2017). "Vital signs: changes in opioid prescribing in the United States, 2006–2015." MMWR. Morbidity and Mortality Weekly Report report 66(26): 697.

Harris, Matthew C., Lawrence M. Kessler, Matthew N. Murray, and Beth Glenn. 2019. “Prescription opioids and labor market pains: The effect of Schedule II opioids on labor force participation and unemployment.” Journal of Human Resources, forthcoming.

Havens, J. R., C. G. Leukefeld, A. M. DeVeaugh-Geiss, P. Coplan and H. D. Chilcoat (2014). "The impact of a reformulation of extended-release oxycodone designed to deter abuse in a sample of prescription opioid abusers." Drug and alcohol dependence 139: 9-17.

Hollingsworth, A., C. J. Ruhm, and K. Simon. (2017). “Macroeconomic Conditions and Opioid Abuse.” National Bureau of Economic Research (NBER) Working Paper 23192.

Horwitz, Jill, Corey S. Davis, Lynn S. McClelland, Rebecca S. Fordon, and Ellen Meara (2018). “The problem of data quality in analyses of opioid regulation: The case of prescription drug monitoring programs.” NBER Working Paper 24947.

Huang, S., et al. (2011). "The long-term effects of childhood maltreatment experiences on subsequent illicit drug use and drug-related problems in young adulthood." Addictive behaviors **36**(1-2): 95-102.

Jaudes, Paula Kienberger, Edem Ekwo, and John Van Voorhis. "Association of drug abuse and child abuse." *Child abuse & neglect* 19.9 (1995): 1065-1075.

Kelleher, K., et al. (1994). "Alcohol and drug disorders among physically abusive and neglectful parents in a community-based sample." American journal of public health **84**(10): 1586-1590.

Kelley, Susan J. "Parenting stress and child maltreatment in drug-exposed children." *Child abuse & neglect* 16.3 (1992): 317-328.

Kelley, Susan J. "Child maltreatment in the context of substance abuse." *The APSAC handbook on child maltreatment* 2 (2002): 105-117.

Lansford, J., Dodge, K., Pettit, G., Bates, J., Crozier, J., & Kaplow, J. (2002). A 12-year prospective study of the long-term effects of early child physical maltreatment on psychological, behavioral, and academic problems in adolescence. Archives of Pediatrics and Adolescent Medicine, 156, 824–830.

Larochelle, M. R., F. Zhang, D. Ross-Degnan and J. F. Wharam (2015). "Rates of Opioid Dispensing and Overdose After Introduction of Abuse-Deterrent Extended-Release Oxycodone and Withdrawal of Propoxyphene Effect of Abuse-Deterrent Oxycodone Introduction and Propoxyphene Withdrawal Effect of Abuse-Deterrent Oxycodone Introduction and Propoxyphene Withdrawal." JAMA Internal Medicine 175(6): 978-987.

Leeb, R., Paulozzi, L., Melanson, C., Simon, T., & Arias, I. (2008). *Child maltreatment surveillance: Uniform definitions for public health and recommended data elements*. Centers for Disease Control and Prevention (CDC).

Lindo, J., and J. Schaller. (2014). "Economic determinants of child maltreatment." Encyclopedia of Law and Economics.

Lynch, Sean, et al. "Trends in infants reported to child welfare with neonatal abstinence syndrome (NAS)." *Children and Youth Services Review* 86 (2018): 135-141.

Mallatt, J. (2018). "The effect of prescription drug monitoring programs on opioid prescriptions and heroin crime rates." September 13. Available at http://dx.doi.org/10.2139/ssrn.3050692

Nelson, L., D. Juurlink, and J. Perrone (2015). Addressing the opioid epidemic. Journal of the American Medical Association 314 (14), 1453-1454.

Nguyen, Thuy D., W. David Bradford, and Kosali I. Simon. *How do Opioid Prescribing Restrictions Affect Pharmaceutical Promotion? Lessons from the Mandatory Access Prescription Drug Monitoring Programs*. No. w26356. National Bureau of Economic Research, 2019

Orsi, R., P. Yuma-Guerrero, K. Sergi, A. A. Pena, and A. M. Shillington. (2018). "Drug overdose and child maltreatment across the United State's rural-urban continuum." Child Abuse & Neglect 86: 358-367.

OxyContin Medication Guide. (2015). Accessed April 5, 2019: https://www.fda.gov/downloads/drugs/drugsafety/ucm208530.pdf

Phillips, D. M. (2000). "JCAHO Pain Management Standards Are Unveiled." JAMA 284(4): 428-429.

Pollini, R. A., Banta-Green, C. J., Cuevas-Mota, J., Metzner, M., Teshale, E., & Garfein, R. S. (2011). "Problematic use of prescription-type opioids prior to heroin use among young heroin injectors." Substance abuse and rehabilitation, 2, 173.

Powell, David, Abby Alpert, and Rosalie L. Pacula. 2018. "A Transitioning Epidemic: How the Opioid Crisis Is Driving the Rise in Hepatitis C." *Health Affairs* 38(2): 287-294.

Powell, David, Rosalie Liccardo Pacula, and Mireille Jacobson. 2018. "Do medical marijuana laws reduce addictions and deaths related to pain killers?" *Journal of Health Economics* 58: 29-42.

Quast, T. (2018). "State-level variation in the relationship between child removals and opioid prescriptions." *Child Abuse & Neglect*: 306-313.

Quast, T., E. A. Storch and S. Yampolskaya (2018). "Opioid prescription rates and child removals: evidence from Florida." Health Affairs 37(1): 134-139.

Quinones, S. (2015). Dreamland: The true tale of America's opiate epidemic. Bloomsbury Publishing USA.

Quinton, S. (2015). "How heroin is hitting the foster care system." Stateline, The Pew Charitable Trusts. Accessed March 10, 2019: https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2015/10/09/how-heroin-is-hitting-the-foster-care-system

Patrick, S. W., R. E. Schumacher, B. D. Benneyworth, E. E. Krans, J. M. McAllister, and M. M. Davis (2012). Neonatal abstinence syndrome and associated health care expenditures: United states, 2000-2009. Journal of the American Medical Association 307 (18), 1934-1940.

Paxon, C., and J. Waldfogel (1999). "Parental resources and child abuse and neglect." *American Economic Review* 89(2): 239-244.

Peterson, C., C. Florence and J. Klevens (2018). "The economic burden of child maltreatment in the United States, 2015." Child abuse & neglect 86: 178-183.

Rosinsky, Kristina, and S.C. Williams (2018). "Child welfare financing SFY 2016: a survey of federal, state, and local expenditures."

Sacks, Daniel W., Alex Hollingsworth, Thuy D. Nguyen, and Kosali I. Simon.. “Can Policy Affect Initiation of Addictive Substance Use? Evidence from Opioid Prescribing.” No. w25974. National Bureau of Economic Research, 2019.

Scholl, L., P. Seth, M. Kariisa, N. Wilson and G. Baldwin (2019). "Drug and Opioid-Involved Overdose Deaths - United States, 2013-2017." MMWR. Morbidity and mortality weekly report 67(5152): 1419-1427.

Schwartz RP, Gryczynski J, O’Grady KE, et al. Opioid agonist treatments and heroin overdose deaths in Baltimore, Maryland, 1995-2009. American Journal of Public Health 2013; 103: 917-922.

Senate Hearing 107-287 (2002). OxyContin: balancing risks and benefits. Hearing of the Committee on Health, Education, Labor, and Pensions, United States Senate.

Sessler, N. E., J. M. Downing, H. Kale, H. D. Chilcoat, T. F. Baumgartner and P. M. Coplan (2014). "Reductions in reported deaths following the introduction of extended-release oxycodone (OxyContin) with an abuse-deterrent formulation." pharmacoepidemiology and drug safety 23(12): 1238-1246.

Severtson, S. G., B. B. Bartelson, J. M. Davis, A. Muñoz, M. F. Schneider, H. Chilcoat, Coplan, S. P.M., H. and R. C. Dart (2013). "Reduced abuse, therapeutic errors, and diversion following reformulation of extended-release oxycodone in 2010." The Journal of Pain 14(10): 1122-1130.

Solowiij, N., and R. Battisti. (2008). “The chronic effects of cannabis on memory in humans: a review.” Current Drug Abuse Review 1(1): 81-98.

Soyka, Michael. "Treatment of opioid dependence with buprenorphine: current update." *Dialogues in clinical neuroscience* 19.3 (2017): 299.

Spatz Widom, C., et al. (2006). "Childhood victimization and illicit drug use in middle adulthood." Psychology of Addictive Behaviors **20**(4): 394.

Stanley, J. and C. Goddard (2004). "Multiple forms of violence and other criminal activities as an indicator of severe child maltreatment." Child Abuse Review: Journal of the British Association for the Study and Prevention of Child Abuse and Neglect **13**(4): 246-262.

Stein. P., and L. Bever. (2017). “The opioid crisis is straining the nation’s foster-care systems.” The Washington Post, July 1. Accessed August 20, 2018: https://www.washingtonpost.com/national/the-opioid-crisis-is-straining-the-nations-foster-care-systems/2017/06/30/97759fb2-52a1-11e7-91eb-9611861a988f_story.html?noredirect=on&utm_term=.41a16065da50

Stith, Sandra M., et al. "Risk factors in child maltreatment: A meta-analytic review of the literature." *Aggression and violent behavior* 14.1 (2009): 13-29.

Substance Abuse and Mental Health Services Administration. (2010). “Results from the 2009 National Survey on Drug Use and Health: Volume I. Summary of National Findings.” Office of Applied Studies, NSDUH Series H-38A, HHS Publication No. SMA 10-4586Findings. Rockville, MD.

Swanson, J. W., et al. (1990). "Violence and psychiatric disorder in the community: evidence from the Epidemiologic Catchment Area surveys." Psychiatric Services **41**(7): 761-770.

Tompkins, D. A., J. G. Hobelmann and P. Compton (2017). "Providing chronic pain management in the “Fifth Vital Sign” Era: Historical and treatment perspectives on a modern-day medical dilemma." Drug and Alcohol Dependence 173: S11-S21.

Tonmyr, L., et al. (2010). "A review of childhood maltreatment and adolescent substance use relationship." Current Psychiatry Reviews **6**(3): 223-234.

U.S. Department of Health & Human Services, Administration for Children and Families, Administration on Children, Youth and Families, Children’s Bureau. (2019). Child Maltreatment 2017. Available from https://www.acf.hhs.gov/cb/resource/child-maltreatment-2017.

Van Zee, A. (2009). "The promotion and marketing of oxycontin: commercial triumph, public health tragedy." American journal of public health 99(2): 221-227.

Vanderploeg, J. J., C. M. Connell, C. Caron, L. Saunders, K. H. Katz and J. Kraemer Tebes (2007). "The impact of parental alcohol or drug removals on foster care placement experiences: A matched comparison group study." Child maltreatment 12(2): 125-136.

Volkow, N. D. (2014). "America’s addiction to opioids: Heroin and prescription drug abuse." Senate Caucus on International Narcotics Control. Washington, DC.

Volkow, ND, Collins FS. The role of science in addressing the opioid crisis. New England Journal of Medicine 2017; 377(4): 391-394.

Von Korff, M., K. Saunders, G. Thomas Ray, D. Boudreau, C. Campbell, J. Merrill, M. D. Sullivan, C. M. Rutter, M. J. Silverberg, C. Banta-Green and C. Weisner (2008). "De facto long-term opioid therapy for noncancer pain." The Clinical journal of pain 24(6): 521-527.

Waldfogel, J. (1998). The Future of Child Protection. Cambridge, MA: Harvard University Press.

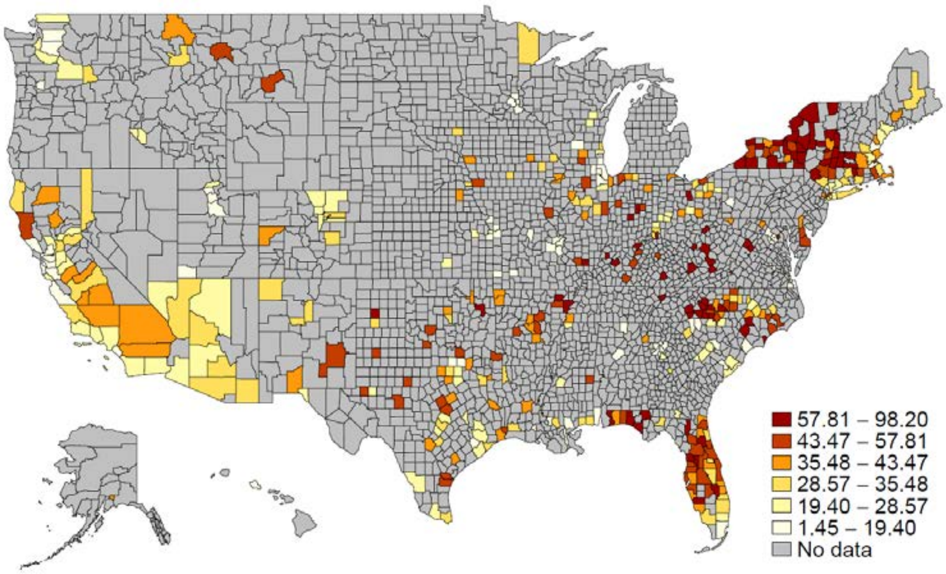
White, H. R. and C. S. Widom (2008). "Three potential mediators of the effects of child abuse and neglect on adulthood substance use among women." Journal of Studies on Alcohol and Drugs **69**(3): 337-347.

Wolock, I., P. Sherman, L. H. Feldman and B. Metzger (2001). "Child abuse and neglect referral patterns: A longitudinal study." Children and Youth Services Review 23(1): 21-47.

World Health Organization. 2016. International statistical classification of diseases and related health problems, tenth revision (ICD–10). 5th ed. Geneva, Switzerland.

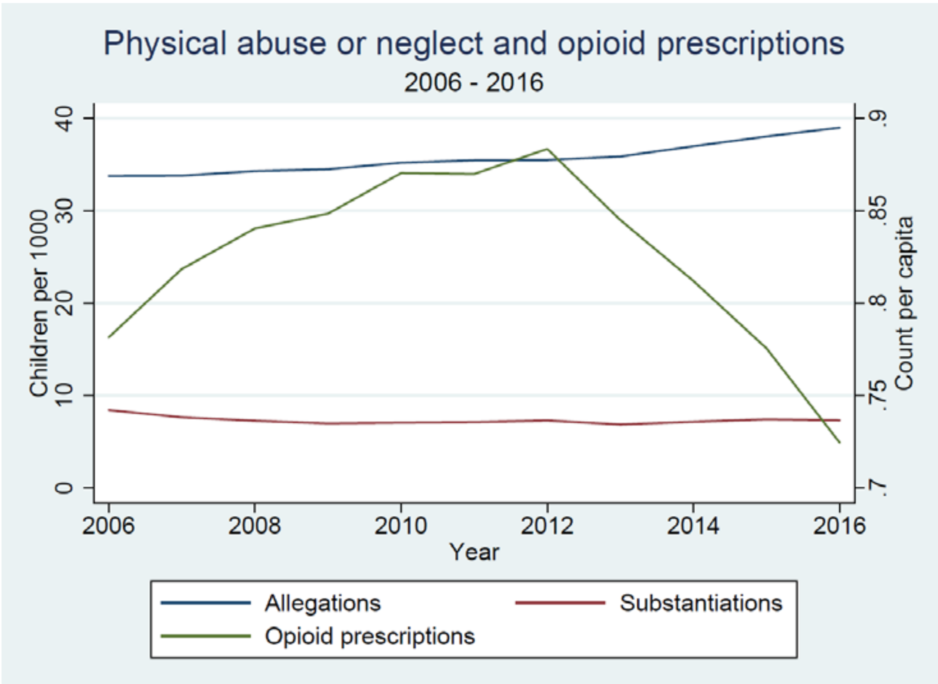
Young, N. K. (2016). Examining the impact of the opioid epidemic, Testimony before the United States Senate Committee on Homeland Security and Governmental Affairs.

Figure 1. Allegations of physical abuse or neglect by sample county, 2006-2016



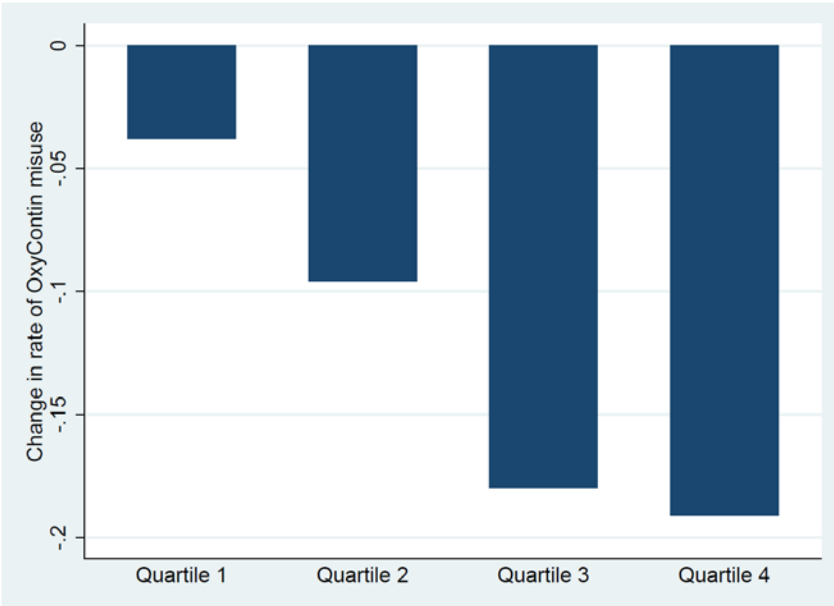
Notes: Figure shows the median number of children per 1000 with physical abuse or neglect allegations by county between 2006 and 2016 for 438 sample counties. Counties in grey not represented in the sample. Shading reflects quantiles of the distribution.

Figure 2. Child abuse and neglect allegations, substantiations, and opioid prescriptions



Notes: Figure depicts annual medians based on 438 sample counties. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Opioid prescriptions are measured as the population-weighted mean per capita opioid prescriptions in the county.

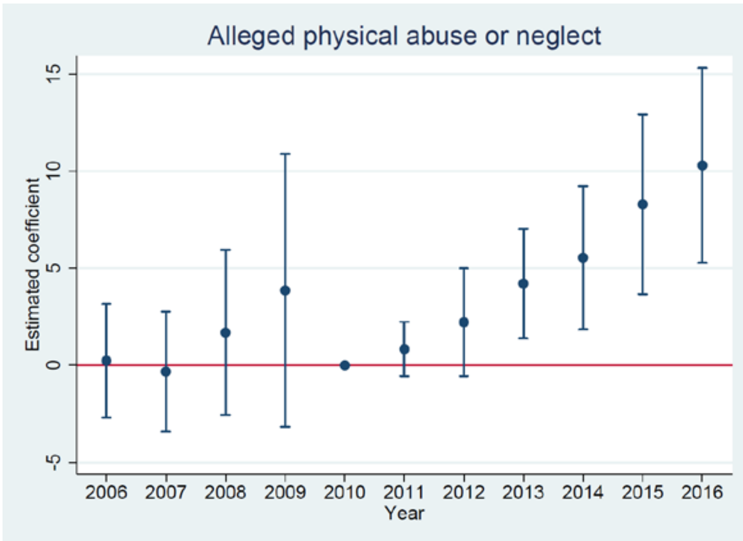
Figure 3. OxyContin analysis: Relationship between pre-intervention exposure and the change in OxyContin misuse between 2008 and 2012



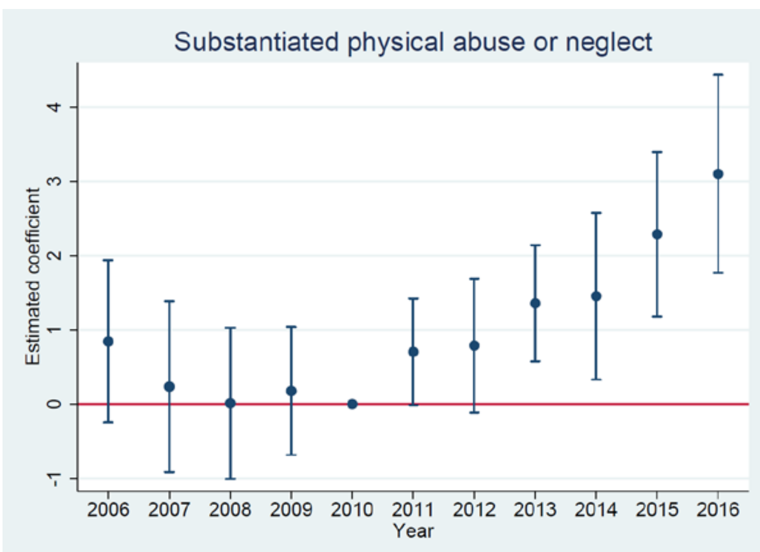
Notes: Quartiles are formed based on the population-weighted mean per capita opioid prescriptions in the county for the period 2006 to 2009 (i.e., pre-intervention exposure). Quartile 1 includes the 110 counties with the lowest mean exposure while quartile 4 includes the 109 counties with the highest mean exposure. The figure shows larger reductions in the state-level population-weighted mean rate of OxyContin misuse between 2008 and 2012 in counties with higher pre-intervention exposure.

Figure 4. OxyContin analysis: Event study results for physical abuse or neglect

Panel A. Alleged physical abuse and neglect



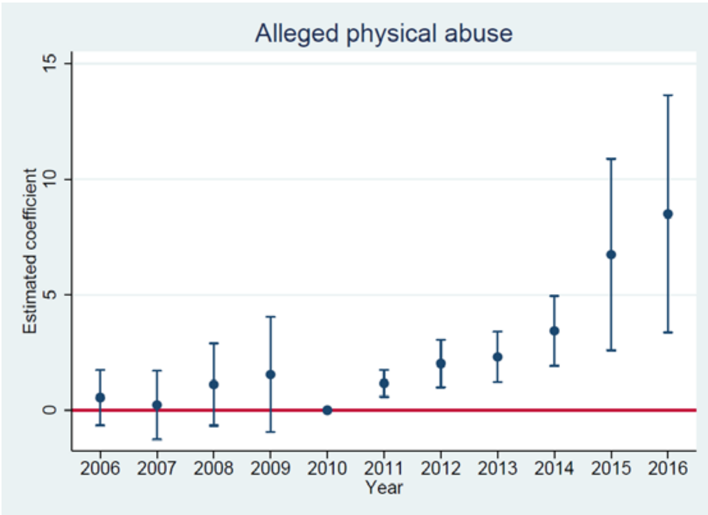
Panel B. Substantiated physical abuse and neglect



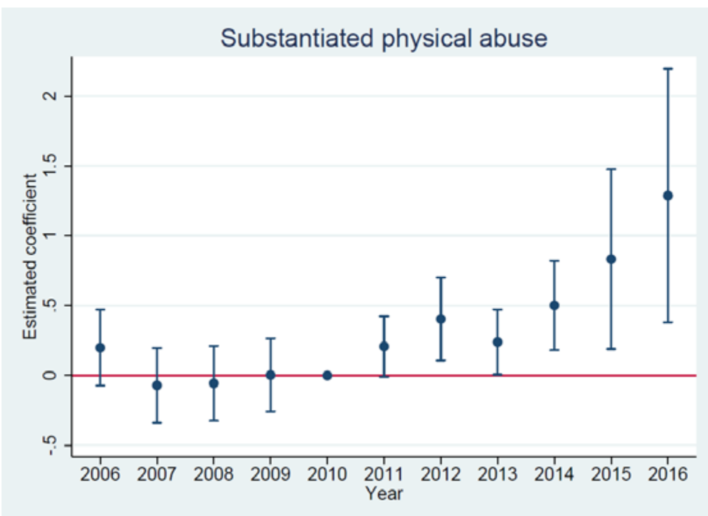
Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009. Standard errors reflect clustering on county with 438 clusters.

Figure 5. OxyContin analysis—event study results for physical abuse

Panel A. Alleged physical abuse



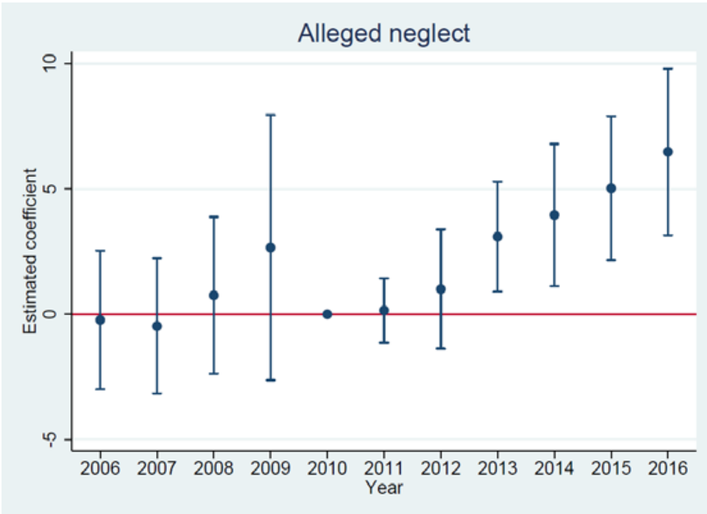
Panel B. Substantiated physical abuse



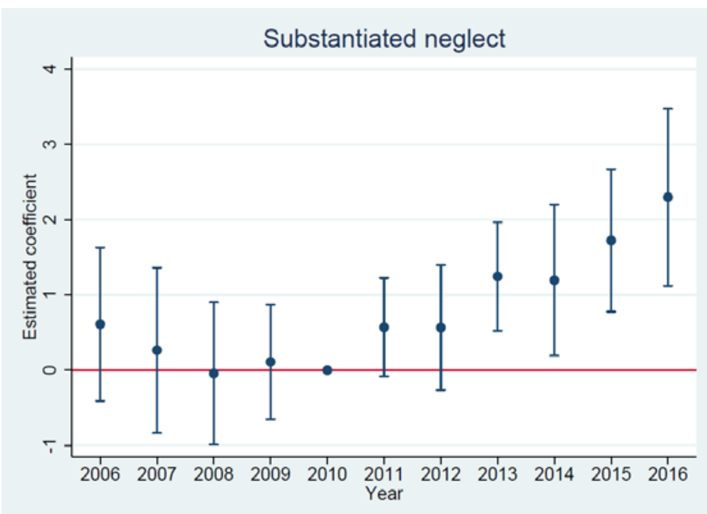
Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Alleged physical abuse refers to the number of children per 1000 with at least one allegation of physical abuse. Substantiated physical abuse refers to the number of children per 1000 with at least one substantiated case of physical abuse. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009. Standard errors reflect clustering on county with 438 clusters.

Figure 6. OxyContin analysis—event study results for neglect

Panel A. Alleged neglect



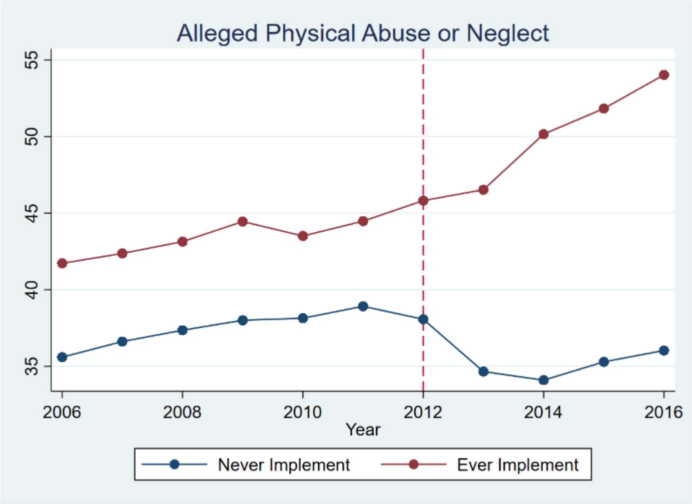
Panel B. Substantiated neglect



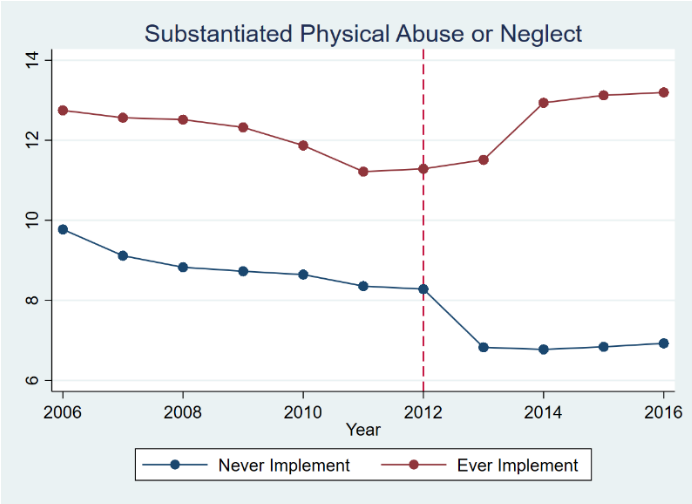
Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Alleged neglect refers to the number of children per 1000 with at least one allegation of neglect. Substantiated neglect refers to the number of children per 1000 with at least one substantiated case of neglect. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009. Standard errors reflect clustering on county with 438 clusters.

Figure 7. PDMP analysis—Descriptive evidence on parallel trends

Panel A: Allegations



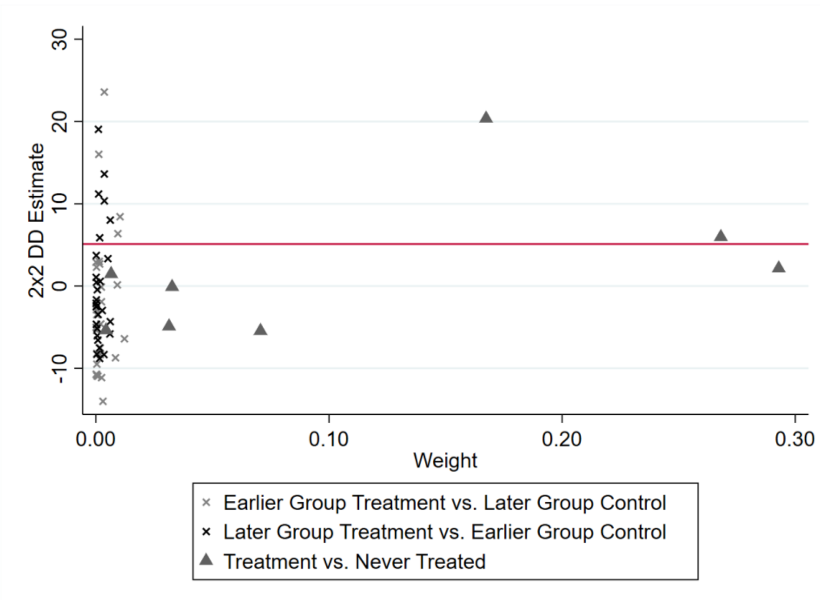
Panel B: Substantiations



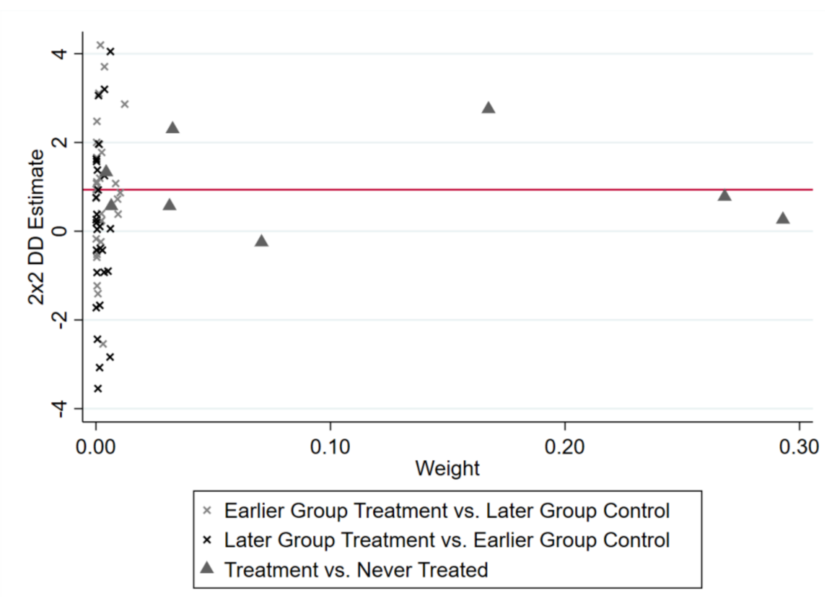
Notes: Plots measure the average number of allegations (substantiations) among counties in states that never implemented a must-access PDMP (in blue) and counties in states that implemented a must-access PDMP (in red). Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. A vertical line at the year 2012 denotes the year in which must-access PDMPs came online in earnest. Prior to 2012 only 3 states had implemented MA-PDMPs, while 5 state implemented in 2012 and 9 state implemented between 2013 and 2015 (see Apendix Table A3).

Figure 8. PDMP analysis—Plots of Goodman-Bacon decomposed 2x2 DD estimates

Panel A: Allegations



Panel B: Substantiations



Notes: The figure reflects the results of the Bacon decomposition on estimates from a model with state and year fixed effects using the full sample. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect.

Table 1. Differences in the pre-intervention period between low- and high-exposure counties

Variable	Low-exposure counties	High-exposure counties	p-value	Data source
Allegations	33.387	40.110	0.000	NCANDS
Substantiations	8.994	9.206	0.743	NCANDS
Per capita opioid prescriptions	0.622	1.132	0.000	CDC
State OxyContin misuse rate	0.523	0.650	0.000	Alpert et al.
% White	80.353	82.770	0.062	Census
% Black	11.522	12.419	0.443	Census
% Hispanic	17.757	8.174	0.000	Census
% Rural	20.051	25.447	0.003	Census
% Female	50.614	51.007	0.000	Census
% Under age 20	28.048	26.696	0.000	Census
% Age 20 to 64	60.122	59.219	0.001	Census
% Over age 64	11.829	14.085	0.000	Census
Unemployment rate	5.997	6.142	0.353	BLS
Labor force participation rate	63.741	61.449	0.000	BLS
Cancer deaths per 100,000 population	174.821	218.528	0.000	CDC

Notes: Table reports means for the pre-reformulation period, 2006-2009, after breaking the sample based on pre-intervention exposure to prescription opioids. Low-exposure (high-exposure) counties are the 219 (219) counties with population-weighted per capita opioid prescriptions for 2006 to 2009 below (at or above) the sample median of 0.825. The fourth column reports p-values for equality of means tests. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect.

Table 2. OxyContin analysis—results of trend-break specification for allegations of physical abuse or neglect

Allegations	(1)	(2)	(3)
Panel A. Estimated coefficients from equation (2)			
δ_1	-1.75 (2.324)	-1.73 (2.314)	-1.758 (2.301)
δ_2	0.372 (0.570)	0.086 (0.574)	0.093 (0.577)
δ_3	1.540* (0.816)	1.573* (0.833)	1.562* (0.866)
Panel B. Implied effects			
1-year effect (δ_1)	-1.75 (2.324)	-1.73 (2.314)	-1.758 (2.301)
2-year effect ($\delta_1 + \delta_3$)	-0.209 (2.884)	-0.157 (2.907)	-0.196 (2.923)
3-year effect ($\delta_1 + 2\delta_3$)	1.331 (3.546)	1.416 (3.596)	1.366 (3.646)
4-year effect ($\delta_1 + 3\delta_3$)	2.870 (4.261)	2.989 (4.336)	2.928 (4.421)
5-year effect ($\delta_1 + 4\delta_3$)	4.410 (5.007)	4.562 (5.105)	4.490 (5.224)
County- and time-varying covariates	No	Yes	Yes
State- and time-varying policy controls	No	No	Yes

Notes: Dependent variable is allegations, the number of children per 1000 with at least one allegation of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county with 438 clusters. Pre-intervention exposure is measured by population-weighted opioid prescriptions per capita in the county, 2006-2009. All specifications include county and year fixed effects. County- and time-varying covariates include percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates. Policy controls include indicator variables for state PDMP and state medical marijuana law. Sample mean (standard deviation) over the period 2006-2009 of allegations is 36.748 (19.197). Sample mean (standard deviation) for pre-intervention exposure to opioid prescriptions is 0.877 (0.353).

Table 3. OxyContin analysis—results of trend-break specification for substantiated cases of physical abuse or neglect

Substantiations	(1)	(2)	(3)
Panel A. Estimated coefficient from equation (2)			
δ_1	0.702 (0.613)	0.661 (0.626)	0.603 (0.618)
δ_2	-0.175 (0.142)	-0.187 (0.156)	-0.179 (0.157)
δ_3	0.648*** (0.229)	0.694*** (0.236)	0.745*** (0.237)
Panel B. Implied effects			
1-year effect (δ_1)	0.702 (0.613)	0.661 (0.626)	0.603 (0.618)
2-year effect ($\delta_1 + \delta_3$)	1.350** (0.659)	1.355** (0.679)	1.348** (0.679)
3-year effect ($\delta_1 + 2\delta_3$)	1.998** (0.772)	2.048** (0.801)	2.093** (0.807)
4-year effect ($\delta_1 + 3\delta_3$)	2.646*** (0.930)	2.742*** (0.966)	2.837*** (0.977)
5-year effect ($\delta_1 + 4\delta_3$)	3.295*** (1.113)	3.436*** (1.156)	3.582*** (1.171)
County- and time-varying covariates	No	Yes	Yes
State- and time-varying policy controls	No	No	Yes

Notes: Dependent variable is substantiations, the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county with 438 clusters. Pre-intervention exposure is measured by population-weighted opioid prescriptions per capita in the county, 2006-2009. All specifications include county and year fixed effects. County- and time-varying covariates include percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates. Policy controls include indicator variables for state PDMP and state medical marijuana law. Sample mean (standard deviation) over the period 2006-2009 of substantiations is 9.100 (6.957). Sample mean (standard deviation) for pre-intervention exposure to opioid prescriptions is 0.877 (0.353). ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 4. OxyContin analysis—results of trend-break specification with heterogeneous effects based on medical marijuana access

Outcome	Allegations		Substantiations	
	Counties with access	Counties without access	Counties with access	Counties without access
Panel A. Estimated coefficients from equation (2)				
δ_1	1.971 (3.165)	-2.062 (2.531)	0.112 (0.908)	0.703 (0.704)
δ_2	0.599 (1.576)	0.019 (0.631)	0.001 (0.300)	-0.167 (0.171)
δ_3	-0.877 (2.364)	1.733* (0.923)	0.342 (0.641)	0.698*** (0.260)
Panel B. Implied effects				
1-year effect (δ_1)	1.971 (3.165)	-2.062 (2.531)	0.112 (0.908)	0.703 (0.704)
2-year effect ($\delta_1 + \delta_3$)	1.094 (4.678)	-0.330 (3.226)	0.454 (1.216)	1.401* (0.756)
3-year effect ($\delta_1 + 2\delta_3$)	0.217 (6.704)	1.403 (4.013)	0.796 (1.719)	2.099** (0.885)
4-year effect ($\delta_1 + 3\delta_3$)	-0.660 (8.898)	3.136 (4.849)	1.138 (2.292)	2.796*** (1.063)
5-year effect ($\delta_1 + 4\delta_3$)	-1.537 (11.161)	4.869 (5.712)	1.480 (2.894)	3.494*** (1.270)

Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county. The sample of counties without access to medical marijuana includes 370 unique counties in 35 states. The sample of counties with access to medical marijuana includes 68 counties in 9 states. Pre-reformulation exposure is measured by population-weighted opioid prescriptions per capita in the county, 2006-2009. All specifications include county and year fixed effects, county- and time-varying covariates (percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates), and indicator variable for state PDMP. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 5. OxyContin analysis—results of trend break specification with heterogeneous effects based on buprenorphine access

Outcome	Allegations		Substantiations	
	Counties with access	Counties without access	Counties with access	Counties without access
Panel A. Estimated coefficients from equation (2)				
δ_1	-2.031 (2.385)	2.476 (4.478)	0.489 (0.616)	3.795 (2.758)
δ_2	0.208 (0.604)	-2.213* (1.207)	-0.159 (0.162)	-0.886 (0.723)
δ_3	1.510* (0.900)	1.970 (1.186)	0.735*** (0.246)	1.162 (0.858)
Panel B. Implied effects				
1-year effect (δ_1)	-2.031 (2.385)	2.476 (4.478)	0.489 (0.616)	3.795 (2.758)
2-year effect ($\delta_1 + \delta_3$)	-0.521 (3.035)	4.446 (4.782)	1.225* (0.680)	4.958 (3.241)
3-year effect ($\delta_1 + 2\delta_3$)	0.989 (3.789)	6.417 (5.339)	1.960** (0.816)	6.120 (3.856)
4-year effect ($\delta_1 + 3\delta_3$)	2.498 (4.596)	8.387 (6.078)	2.696*** (0.995)	7.283 (4.551)
5-year effect ($\delta_1 + 4\delta_3$)	4.008 (5.432)	10.357 (6.943)	3.431*** (1.198)	8.445 (5.293)

Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county. The sample of counties without access to buprenorphine includes 34 unique counties in 13 states. The sample of counties with access to buprenorphine includes 404 counties in 44 states. Pre-reformulation exposure is measured by population-weighted opioid prescriptions per capita in the county, 2006-2009. All specifications include county and year fixed effects, county- and time-varying covariates (percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates), and indicator variables for state PDMP and state medical marijuana legislation. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 6. PDMP analysis—difference-in-differences (DD) results

Sample	Allegations		Substantiations	
Full sample	5.109*** (0.949)	4.583*** (0.967)	0.935*** (0.293)	0.838*** (0.312)
Counties with pre-intervention exposure at or above the median	5.809*** (1.613)	5.450*** (1.499)	1.079** (0.467)	0.971** (0.477)
Counties with pre-intervention exposure below the median	4.663*** (0.923)	3.905*** (1.050)	0.864** (0.346)	0.643* (0.384)
Control Variables	No	Yes	No	Yes

Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. All models include year and county fixed effects. Additional county-level controls: percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates. Standard errors (in parentheses) reflect clustering on county. Pre-intervention exposure is measured by population weighted opioid prescriptions per capita in the county, 2006-2009. Full sample contains 4,818 observations. Split samples contain 2,409 observations each. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 7. PDMP analysis—Bacon decomposition

Treatment-control comparisons	Weight	Average DD estimate	
		Allegations	Substantiations
Earlier treated vs. later control	0.076	-0.375	1.196
Later treated vs. earlier control	0.05	1.078	0.215
Treated vs. never treated	0.874	5.817	0.953

Notes: We perform the Bacon decomposition on estimates from the full sample model with state and year fixed effects. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect.

Table 8: Sensitivity to must-access PDMP treatment assignment and timing of treatment

Panel A. Baseline from Gihleb et al. (2019)											
	All dates from Gihleb et al.	Remove FL from treatment	Remove TX from treatment	Remove MS from treatment	Add OK to treat-ment	Add GA to treat-ment	Add IN to treat-ment	Add GA & IN to treatment	Change OH from 2011 to 2012	Change MA from 2013 to 2014	Change LA from 2014 to 2008
All allegations	-1.161 (0.727)	0.161 (0.796)	-0.044 (0.802)	-1.466** (0.729)	-1.141 (0.725)	-0.162 (0.738)	1.091 (0.712	2.020*** (0.700)	-1.253* (0.729)	-1.060 (0.730)	-0.855 (0.727)
All substantiations	-0.381 (0.288)	0.742** (0.291)	-0.418 (0.347)	-0.449 (0.292)	-0.231 (0.285)	-0.427 (0.279)	-0.107 (0.279)	-0.159 (0.271)	-0.454 (0.301)	-0.208 (0.309)	-0.439 (0.287)
Panel B. Baseline from Sacks et al. (2019)											
	All dates from Sacks et al.	Add FL to treatment	Add TX to treatment	Add MS to treatment	Remove OK from treat-ment	Remove GA from treat-ment	Remove IN from treat-ment	Remove GA & IN from treatment	Change OH from 2012 to 2011	Change MA from 2014 to 2013	Change LA from 2008 to 2014
All allegations	4.722*** (0.948)	2.593*** (0.764)	2.776*** (0.776)	4.943*** (0.912)	4.362*** (0.960)	4.855*** (0.978)	4.786*** (0.943)	0.707 (0.892)	3.620*** (0.982)	4.573*** (0.937)	1.965** (0.892)
All substantiations	1.227*** (0.339)	-0.0394 (0.330)	1.005*** (0.297)	1.269*** (0.333)	1.304*** (0.341)	1.073*** (0.347)	1.303*** (0.31772)	1.046*** (0.362)	1.347*** (0.351)	1.005*** (0.324)	0.927*** (0.348)

Notes: All allegations reflect the number of children per 1000 with at one least maltreatment allegation (of any type). All substantiations reflect the number of children per 1000 with at least one substantiated maltreatment case (of any type). All models include year and county fixed effects. Standard errors (in parentheses) reflect clustering on county. Sample size is 4818. Must-access PDMP dates from Gihleb et al. (2019): Delaware (2012), Florida (2011), Kentucky (2012), Louisiana (2014), Massachusetts (2013), Mississippi (2011), New Mexico (2012), Nevada (2007), New York (2013), Ohio (2011), Tennessee (2013), Texas (2009), Vermont (2013), West Virginia (2012) . Must-access PDMP dates from Sacks et al. (2019) are presented in Table C1.

.

FOR ONLINE PUBLICATION

APPENDIX A – Super counties, supplementary information on sample, and additional event study results

Construction of super counties

To construct child abuse and neglect measures for each super county, the basic idea is to take the state-level totals and subtract the sum of the county-level totals for all of the counties already represented in the balanced panel that comprises our sample. In what follows, we refer to the counties represented in our balanced panel as "identified" (i.e., in the NCANDS data). Table A3 lists the number of identified counties by state.[47] For a given state, all other counties (i.e., the non-identified counties) will be part of the super county.

We begin by forming state-level child abuse and neglect measures: (i) the number of children who were the subject of a abuse and neglect allegation in each report year and state, and (ii) the number of children considered to be victims of abuse and neglect in each report year and state (i.e. substantiations). By construction, these state-level measures count children more than once if they are the subject of an allegation/a victim in more than one county in the state in the report year. This feature is necessary for forming the super county abuse and neglect measures; otherwise the sum of allegations/substantiations from all identified counties in the state may exceed the respective state-level measure. For identified counties, the child abuse and neglect measures are the county-level counterparts to the state-level measures. For super counties, the child abuse and neglect measures are the difference between the state-level measure and the sum of the identified county-level measures for each state/report year.

We use a similar technique to form most covariates for the super counties. For the percent rural and cancer crude rate variables, the super county covariates reflect the (unweighted) mean value for the non-identified counties in the state. While the panel of identified counties is balanced (438 counties from 2006 to 2016), when we add in the super counties we end up with a slightly unbalanced panel. This is because ND is not represented until 2009 and OR is not represented until 2011 (i.e., the states did not report to NCANDS prior to these years).

[47] MD, MI, ND, OR, RI, VT, and WY have zero identified counties. Thus, for these states, the super county represents the entire state.

Table A1. Sample summary statistics and comparison to excluded counties

Mean (standard deviation)	Counties included in balanced panel sample	Excluded counties	p-value for difference of means test
Opioid prescriptions per capita	0.875 (0.343)	0.870 (0.497)	0.483
% White	80.777 (13.696)	86.402 (16.556)	0.000
% Black	12.167 (12.285)	8.607 (14.816)	0.000
% Hispanic	13.799 (15.467)	7.617 (12.664)	0.000
% Rural	21.267 (18.746)	65.230 (28.511)	0.000
% Female	50.787 (1.097)	49.870 (2.340)	0.000
% Under age 20	26.555 (3.325)	25.716 (3.565)	0.000
% Age 20 to 64	59.472 (2.956)	57.356 (3.409)	0.000
% Over age 64	13.972 (4.377)	16.928 (4.291)	0.000
Unemployment rate	6.829 (2.734)	6.821 (2.988)	0.869
Labor force participation rate	61.069 (6.070)	59.294 (9.161)	0.000
Cancer crude rate	197.511 (52.263)	243.486 (62.808)	0.000
Number of unique counties	438	2705	--

Notes: Means are taken over the sample period, 2006 to 2016. There are some missing values for opioid prescriptions per capita in counties excluded from our sample so 2545 unique counties are used to calculate the “excluded counties” mean for this variable.

Table A2. Number of counties in each state represented in the balanced panel

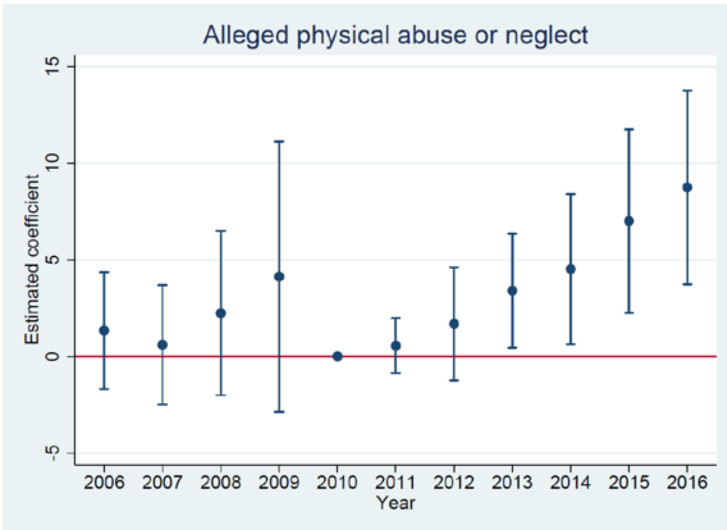
State abbreviation	Number of counties represented in sample
AK	1
AL	3
AR	11
AZ	8
CA	34
CO	9
CT	6
DC	1
DE	3
FL	42
GA	10
HI	1
IA	7
ID	2
IL	18
IN	11
KS	4
KY	9
LA	8
MA	11
ME	4
MN	5
MO	11
MS	5
MT	4
NC	32
NE	2
NH	3
NJ	1
NM	5
NV	2
NY	46
OH	17
OK	5
PA	2
SC	11

SD	1
TN	2
TX	44
UT	5
VA	11
WA	8
WI	6
WV	7
Total	438

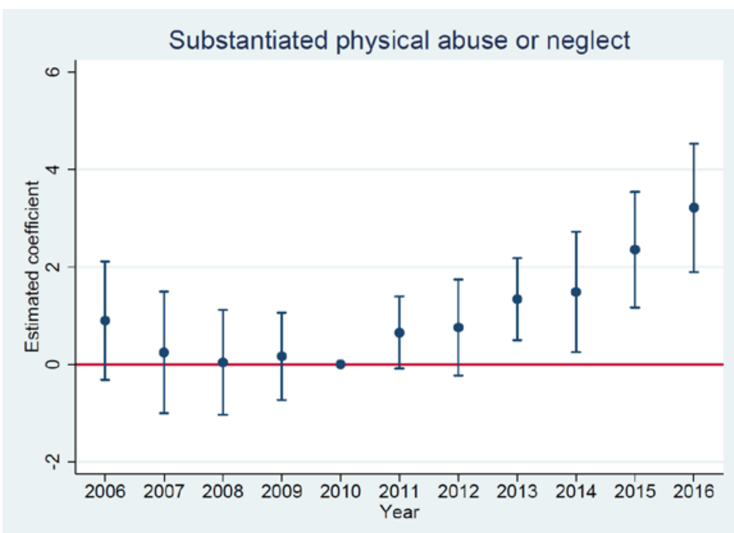
Notes: The following states have zero counties represented in our sample: MD, MI, ND, OR, RI, VT, WY.

Figure A1. OxyContin analysis—event study results with controls

Panel A. Alleged physical abuse or neglect



Panel B. Substantiated physical abuse or neglect

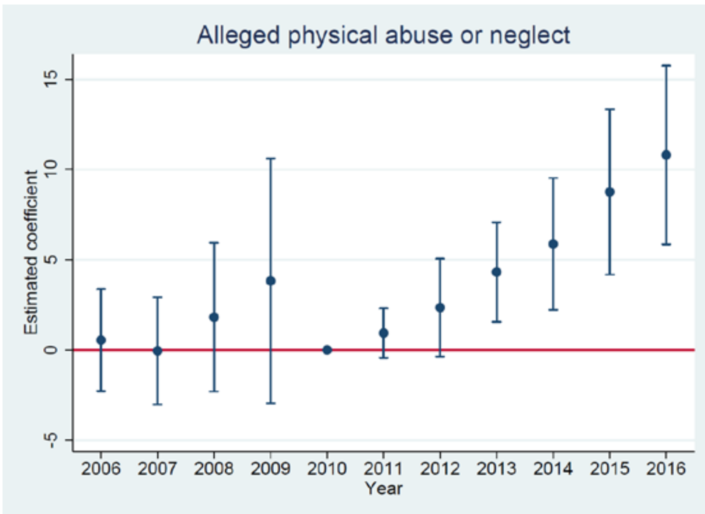


Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009. Standard errors are clustered on county. Specifications include county and year fixed effects; percent female population; percent Black population; percent

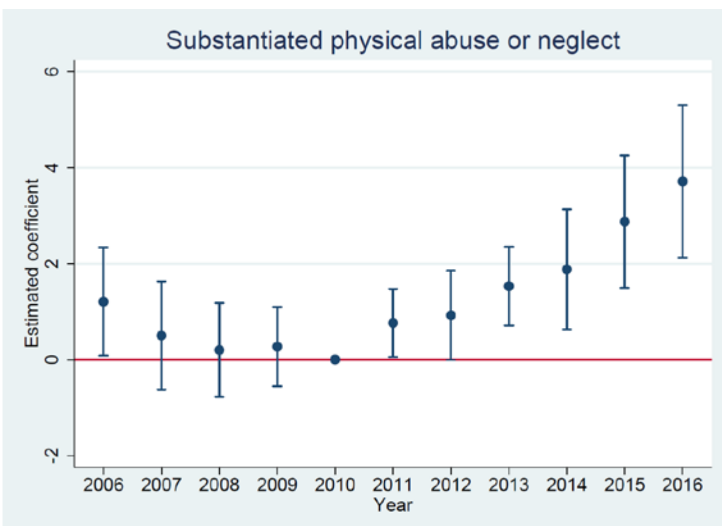
Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates.

Figure A2. OxyContin analysis: Event study results with sample augmented to include super counties

Panel A. Alleged physical abuse or neglect



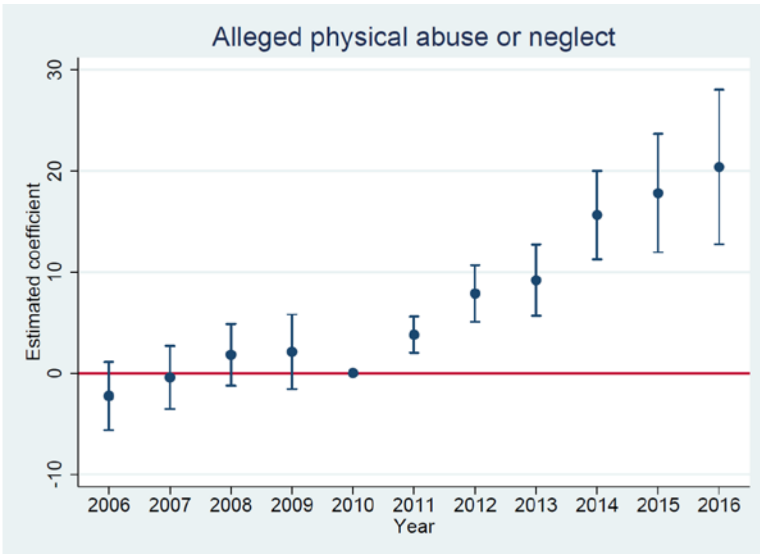
Panel B. Substantiated physical abuse or neglect



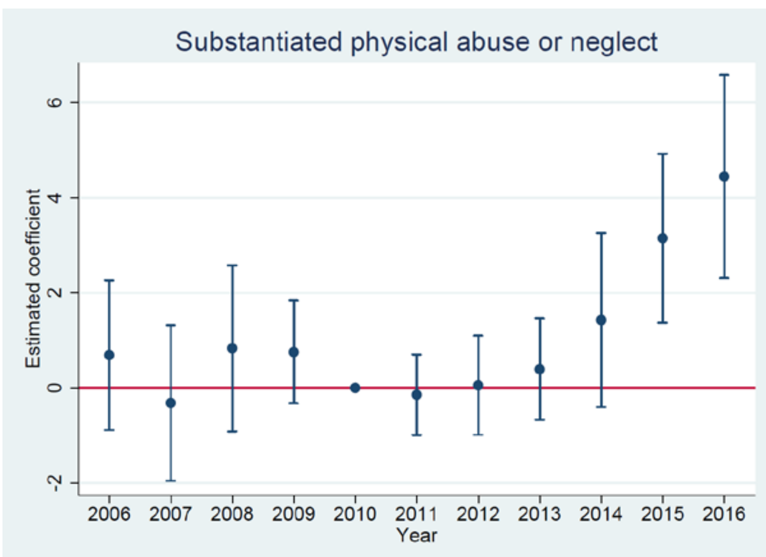
Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors reflect clustering on county with 486 clusters. Sample consists of the 438 counties included in our balanced panel and 48 super counties. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009.

Figure A3. OxyContin analysis: Event study results with Alpert et al.'s (2018) pre-intervention exposure measure

Panel A. Alleged physical abuse or neglect



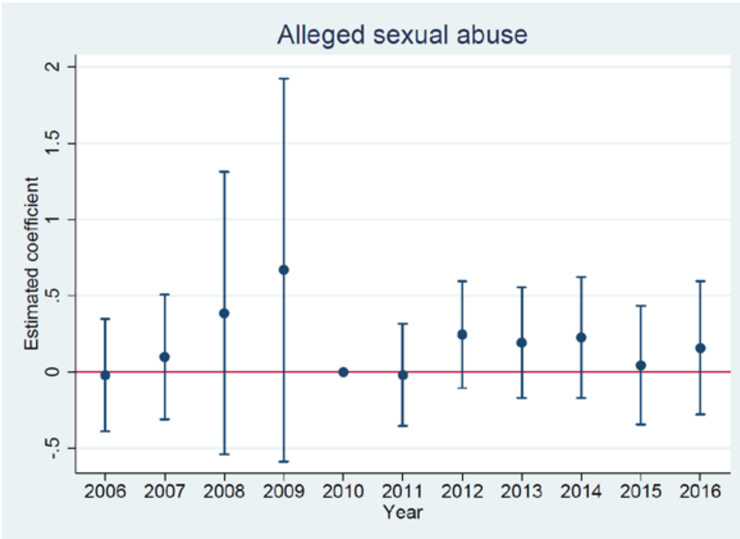
Panel B. Substantiated physical abuse or neglect



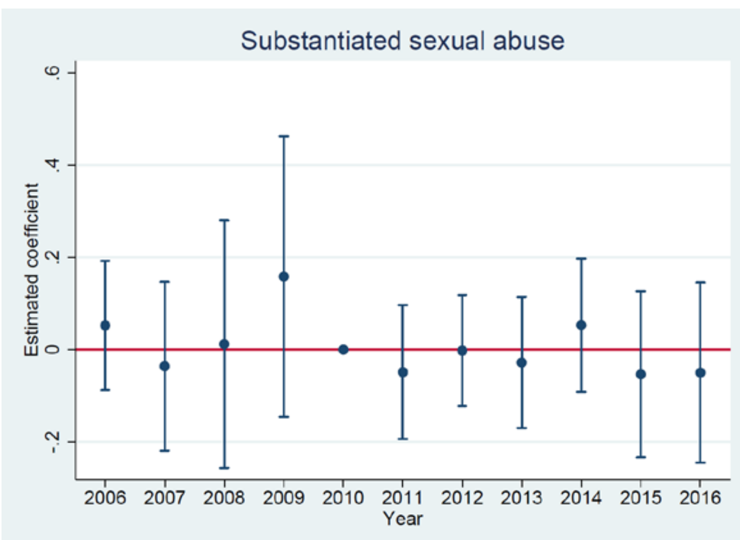
Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Pre-reformulation exposure is measured by the population-weighted rate of OxyContin misuse in the state, 2004-2009 (Alpert et al., 2018). Standard errors reflect clustering on county with 438 clusters.

Figure A4. OxyContin analysis—event study results for sexual abuse

Panel A. Alleged sexual abuse



Panel B. Substantiated sexual abuse



Notes: Each figure reports point estimates and 95% confidence intervals on the interaction terms from specification (1) with 2010, the year in which OxyContin was reformulated, normalized to zero. Alleged sexual abuse refers to the number of children per 1000 with at least one allegation of sexual abuse. Substantiated sexual abuse refers to the number of children per 1000 with at least one substantiated case of sexual abuse. Pre-intervention exposure is measured as the population-weighted average of per capita prescription opioids in the county from 2006 to 2009. Standard errors reflect clustering on county with 438 clusters.

FOR ONLINE PUBLICATION

APPENDIX B – Supplementary trend break results

Table B1. OxyContin analysis—results of trend-break specification with sample augmented to include super counties

Outcome	Allegations	Substantiations
Panel A. Estimated coefficients from equation (2)		
δ_1	-1.711 (2.213)	0.692 (0.614)
δ_2	0.060 (0.557)	-0.311* (0.160)
δ_3	1.658** (0.839)	0.967*** (0.253)
Panel B. Implied effects		
1-year effect (δ_1)	-1.711 (2.213)	0.692 (0.614)
2-year effect ($\delta_1 + \delta_3$)	-0.053 (2.813)	1.659** (0.697)
3-year effect ($\delta_1 + 2\delta_3$)	1.604 (3.512)	2.626*** (0.850)
4-year effect ($\delta_1 + 3\delta_3$)	3.262 (4.262)	3.593*** (1.043)
5-year effect ($\delta_1 + 4\delta_3$)	4.920 (5.041)	4.560*** (1.257)

Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county with 486 clusters. Pre-reformulation exposure is measured by population-weighted opioid prescriptions per capita in the county, 2006-2009. All specifications include county and year fixed effects, county- and time-varying covariates (percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates), and indicator variables for state PDMP and state medical marijuana law. Sample mean (standard deviation) over the period 2006-2009 for allegations, substantiations, and opioid prescriptions per capita is 36.070 (19.014), 10.832 (9.939), and 0.871 (0.342), respectively. ***Significant at 1% level. **Significant at 5% level.

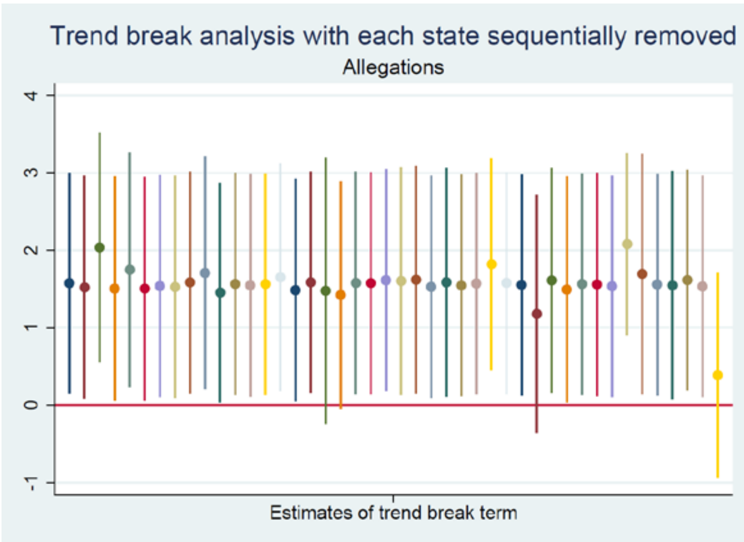
Table B2. OxyContin analysis—results of trend break specification with Alpert et al.'s (2018) pre-intervention exposure measure

Outcome	Allegations	Substantiations
Panel A. Estimated coefficients from equation (2)		
δ_1	2.039 (1.685)	-1.075* (0.638)
δ_2	0.166 (0.519)	-0.150 (0.221)
δ_3	3.197** (0.917)	1.056** (0.406)
Panel B. Implied effects		
1-year effect (δ_1)	2.039 (1.685)	-1.075* (0.638)
2-year effect ($\delta_1 + \delta_3$)	5.235** (2.036)	-0.020 (0.692)
3-year effect ($\delta_1 + 2\delta_3$)	8.432*** (2.671)	1.036 (0.938)
4-year effect ($\delta_1 + 3\delta_3$)	11.628*** (3.436)	2.092* (1.268)
5-year effect ($\delta_1 + 4\delta_3$)	14.825*** (4.261)	3.148* (1.633)

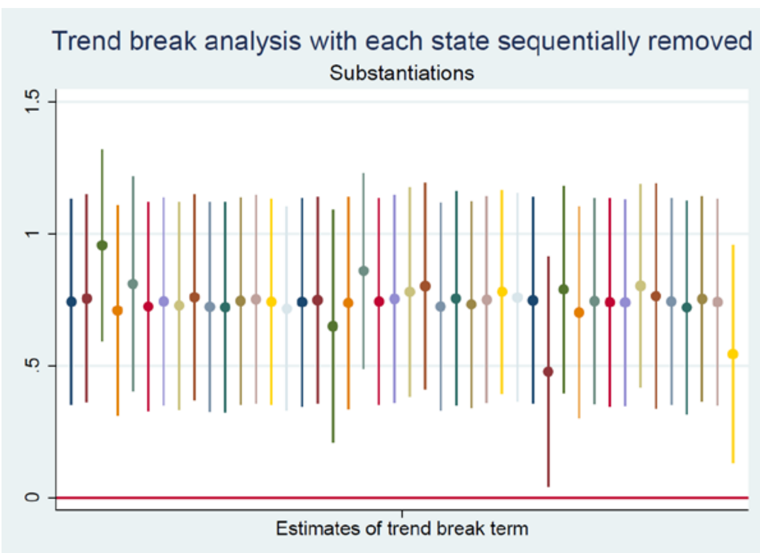
Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Standard errors (in parentheses) reflect clustering on county with 438 clusters. Pre-reformulation exposure is measured by the population-weighted rate of OxyContin misuse in the state, 2004-2009. All specifications include county and year fixed effects, county- and time-varying covariates (percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates), and indicator variables for state PDMP and state medical marijuana law. Sample mean (standard deviation) over the period 2006-2009 of allegations and substantiations is 36.765 (19.201) and 9.102 (6.960), respectively. Sample mean (standard deviation) for initial OxyContin misuse rate is 0.586 (0.229). ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Figure B1. OxyContin analysis—summary of tread break results with all counties from a single state removed sequentially

Panel A. Allegations



Panel B. Substantiations



Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. Figures report the estimated trend break term and 90% confidence intervals from the trend break specification with samples that remove all counties in each state sequentially. Standard errors reflect clustering on county with 438 clusters.

FOR ONLINE PUBLICATION

APPENDIX C. PDMP implementation dates and robustness checks

Table C1. Years in which must-access PDMPs went into effect for adopting states

Year	States				
2007	NV				
2008	LA				
2009					
2010					
2011	OK				
2012	DE	OH	WV	KY	NM
2013	TN	NY	VT		
2014	GA	MA	IN		
2015	VA	CT	NJ		
2016	NH	RI			

Notes: Must-access PDMP implementation dates were taken from Sacks et al. (2019).

Table C2. PDMP analysis—difference-in-differences (DD) results with Alpert et al.'s (2018) pre-intervention exposure measure

Sample	Allegations		Substantiations	
Full Sample	5.109*** (0.949)	4.583*** (0.967)	0.935*** (0.293)	0.838*** (0.312)
Counties with equal to or above pre-intervention exposure	4.046*** (1.324)	3.942*** (1.261)	1.308*** (0.398)	1.256*** (0.421)
Counties with below pre-intervention exposure	5.864*** (1.093)	3.206*** (1.183)	0.273 (0.4339)	-0.397 (0.401)
Control Variables	No	Yes	No	Yes

Notes: Allegations refer to the number of children per 1000 with at least one allegation of physical abuse or neglect. Substantiations refer to the number of children per 1000 with at least one substantiated case of physical abuse or neglect. All models include year and county fixed effects. Additional county-level controls: percent female population; percent Black population; percent Hispanic population; percent rural population; number of cancer deaths per 100,000 population; percent population under age 15, between age 15 and 19, between age 20 and 24, between age 35 to 44, between age 45 to 54, between age 55 to 64, and over age 65; unemployment and labor force participation rates. Robust standard errors, clustered at the county level in parenthesis. In rows 2 and 3 the sample is split based on the median level of the population-weighted rate of OxyContin misuse in the state from 2004-2009. Full sample contains 4,818 observations. Split samples contain 2,409 observations each. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.