The Effect of Mandatory Access Prescription Drug Monitoring Programs on Foster Care Admissions

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Abstract

The opioid epidemic is a national public health emergency. As the number of fatal overdoses and drug abuse skyrocket, children of opioid-dependent parents are at increased risk of being neglected, abused or orphaned. While a few studies have examined the effects of policies restricting prescription drug supply on drug abuse, we know less about the effects these policies may have on children of opioid-dependent parents. This paper estimates the effect of mandatory prescription drug monitoring programs (PDMPs) on child removals. To identify the effects of the programs on foster care admissions, we exploit the variation across states in the timing of adoption of mandatory PDMPs, using an event-study approach as well as standard difference-in-difference models. Consistent with previous evidence examining the effects of PDMPs on drug abuse, we find that operational PDMP did not have any significant effects on foster care admissions. However, the introduction of mandatory provisions reduced child removals by 10%. Exploring the reasons of removals, we show that these effects are driven by the reductions in first removals and cases of child neglect. There is also evidence of significant reductions in removal cases associated with child physical abuse. Effects are strongest among children of young caregivers.

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1 Introduction

The United States is in the midst of an opioid overdose epidemic. Drug mortality rose by 300% between 1999 and 2016. In 2016, the U.S. experienced the largest annual increase in drug overdose deaths ever recorded. Public health officials consider the current opioid epidemic crisis the worst drug crisis in American history. This rapid increase in drug mortality is related to the diffusion of prescription opioids (e.g., Oxycontin) and more recently to the spread of fentanyl, an opioid typically used as a pain medication (Paulozzi et al., 2014; Dart et al., 2015; Ruhm, 2018). The total economic burden of prescription drug abuse is estimated to be 78.5 billion dollars per year (Florence et al., 2016).

As recently highlighted by Quast et al. (2018), a critical aspect of this drug crisis is its effects on the ability of addicted parents to care for their children. In 2015, there were 683,000 victims of child abuse and neglect reported to child protective services (CPS). According to the US Department of Health and Human Services (2015), 25.4% of victims of child abuse were reported with the drug abuse caregiver risk factor and the evidence suggests there is an increase in caregiver drug abuse. Parental neglect and parental drug abuse are the two most common reasons for removals (AFCARS Report, 2015). The opioid epidemic has forced thousands of children from their homes, at risk of being neglected, abandoned, or orphaned by drug-addicted parents. There is increasing concern that America's opioid crisis may overwhelm the US foster case system as thousands of children are taken out of the care of addicted parents.[1]

Foster care numbers have been soaring in many US states. In 2015, 429,000 children were in foster care, a 6.7% increase with respect to 2013. This surge is largely due to the increase in the number of cases related to parental drug-abuse. Figure 1 illustrates how the trend in drug-related child abuses and the number of children in foster because of drug-related abuses closely mirrored the increase in fatal overdoses. From 2000 to 2015 the number of

[1] See https://www.npr.org/2017/12/23/573021632/the-foster-care-system-is-flooded-with-children-of-the-opioid-epidemic.

drug-related foster care admissions have increased by 66% (Figure 2). These increases in the foster care population generate significant monetary and non-monetary costs. The public costs of removing maltreated children are substantial. Annual state and federal expenditures for foster care amount to more than 9 billion dollars, only accounting for Title IV-E of the Social Security Act. Even more funds are spent for publicly subsidized medical care for foster children, Food Stamps, TANF and child care payments to foster care families (Zill, 2011). Previous research estimates that the fiscal costs of a child in foster care are approximately $20,000 (Zill, 2011). These estimates do not account for the detrimental effects of child abuse and foster care on children long-run health and human capital outcomes, substance abuse, and crime (Doyle Jr, 2007, 2008; Currie and Spatz Widom, 2010; Dube et al., 2003).

To address the surge in prescription drug abuse, states have adopted prescription drug monitoring programs (PDMP). These programs track prescriptions, helping in identifying doctor shopping and prescription drug abuse. These programs have been at the center of the policy discussion on the opioid epidemic. Policymakers at the federal and state levels have recommended the implementation of PDMPs and specifically mandating their use by healthcare providers. The Centers for Disease Control and Prevention (CDC) highlights moving towards universal PDMP registration and utilization as one of the priority strategies for states to prevent prescription drug overdoses. The GAO report (US GAO 2009) also stressed that in order for PDMPs to be useful, providers and pharmacies must use the data. Currently, most states have adopted an operational PDMP that does not legally require health professionals to query the database. Only a few states mandate their use since 2007 requiring doctors and pharmacies to query PDMPs before prescribing a controlled substance.

Previous studies found mixed evidence on the effects of operational PDMPs (Kilby, 2015; Mallatt, 2017; Patrick et al., 2016; Simoni-Wastila and Qian, 2012; Meara et al., 2016). Overall, there is a growing consensus that non-mandated PDMPs had small or null effects on drug abuse (Simoni-Wastila and Qian, 2012; Meara et al., 2016), but recent studies suggest that while operational PDMPs were not effective, mandatory PDMPs led to significant reductions in drug abuse (Buchmueller and Carey, 2018; Dave et al., 2017). The main contribution of this study is to evaluate the effects of prescription drug monitoring programs on child removals. While several studies have examined the effects of PDMPs on drug abuse, the best of our knowledge, this is the first study analyzing the effects of prescription drug monitoring programs on foster care admissions.

Despite the growing attention raised by the press reports of state foster systems being overwhelmed by children of opioid-dependents, there is little empirical evidence documenting the relationship between opioid abuse and child removals. Cunningham and Finlay (2013) analyze the effect of methamphetamine use on foster care admissions using an instrumental variable strategy. Their strategy relies on deviations in the real price of meth from national trends caused by large federal supply interdictions that affected meth supply. They find evidence of a positive elasticity of foster care with respect to meth use and showed the limited power of precursor control at combating methamphetamine. One limitation of their study is the limited external validity. The authors focus on a specific drug (d-methamphetamine) and estimate a local average treatment effect relating only to how changing drug use due to changing retail meth prices affect foster care. Using data from Florida counties for the period 2012-2015, Quast et al. (2018) document that an increase in opioid prescription rate was associated in an increase in the removal rate for parental neglect, with the effects largely driven by counties with the highest concentration of whites. Their analysis provides insightful findings, however it is limited by the short sample period, the local nature of the data which may not be representative of the US population, and the small sample size which restricts their ability to control for county-level time-varying confounding factors. In addition, their study did not examine the role of drug monitoring programs in reducing foster care admissions, which is the main contribution of our study.

To identify the effects of PDMPs on foster care admissions we exploit variation in the timing of adoption of operational and mandatory PDMPs across US States using an event-study as well as standard difference-in-difference regression models. Event-study regression models show no significant differences in trends prior to the adoption of Mandatory PDMP. We also control for other state policies and show that the results are not driven by other policies, nor by one particular state. Consistent with previous studies analyzing the effects of PDMPs on drug abuse (Buchmueller and Carey, 2018; Dave et al., 2017), we find no evidence that operational PDMPs had significant effects on foster care admissions, while mandatory-access PDMPs reduced child removals by 10%. The size of the effects is consistent with previous estimates of the effects of mandatory PDMPs on drug abuse (Buchmueller and Carey, 2018; Dave et al., 2017).

The impact of mandatory PDMP is concentrated on first removals, while we find no evidence of significant effects on repeated removals. Our results are largely driven by the reductions in cases of child neglect. However, we also find evidence of reductions in cases associated with child abuse. Consistent with previous evidence on the effects of mandatory PDMP on drug abuse, we find larger effects among children of younger caregivers. We provide a battery of robustness checks supporting a causal interpretation of our findings.

Our results suggest that mandatory PDMPs may reduce foster care costs by $476 million per year. Given the long-lasting implications of child maltreatment and neglect, programs aimed at controlling the supply of prescription drugs may have large long-run returns if effectively enforced.

The paper is organized as follows. Section 2 discusses the background and presents the main data sources. We discuss the empirical specification in Section 3. Results are presented in Section 4. Section 5 concludes.

2 Background and Data

2.1 Prescription Drug Epidemic and Policy Response

According to CDC estimates (Rudd, 2016), the rise in prescription drug use and abuse largely accounts for the trends in drug-related deaths. Previous scholars linked the opioid crisis to the long-run socio-economic decline (Case and Deaton, 2015), documenting its contribution to the reversal in the decline of mid-life all cause mortality over the last 2 decades. In addition, a growing set of studies relates the opioid epidemic to physician behavior and supply-side regulation (Alpert et al., 2017; Pacula et al., 2015; Ruhm, 2018). Among other factors, the market entry of OxyContin in 1996 and the diffusion of aggressive pain management contributed substantially to the surge in opioid use over the last two decades (Laxmaiah Manchikanti et al., 2012). Reports also suggest that most of the individuals at high risk of fatal overdose obtained prescription drugs from physicians, and doctor shopping is considered the main source of supply.

To respond to the dramatic increase in fatal overdoses and drug-abuse, states have introduced several programs to improve opioid prescribing, inform clinical practice and protect patients at risk. Prescription drug monitoring programs (PDMPs) are electronic databases that track controlled substance prescriptions in a state. PDMPs allow health authorities and pharmacies to have timely information about prescribing and patient behaviors. Access to these records can help identify patients who are receiving multiple prescriptions and may contribute to the epidemic. Non-mandated PDMPs do not legally require health professionals to query them. However, since 2007 a few states have now extended their PDMPs with mandatory access provisions which require doctors and pharmacies to query PDMPs before prescribing a controlled substance. Table 1 lists the dates operational and mandatory PDMPs became effective in each state.

Previous studies evaluating the effects of PDMPs on opioid consumption reached different conclusions. There is consensus that PDMPs reduced oxycodone shipments (Kilby, 2015; Mallatt, 2017). The evidence is mixed when focusing on hydrocodone shipments or other abuse outcomes. While some studies found evidence that non-mandated PDMPs decreased fatal non-oxycodone related overdoses and poisonings (Mallatt, 2017; Patrick et al., 2016; Simoni-Wastila and Qian, 2012), most of them found evidence of small or null effects on drug abuse (Simoni-Wastila and Qian, 2012; Meara et al., 2016). However, recent papers focusing on the effects of PDMPs mandates found significant effects on opioid quantity and shopping behavior, abuse outcomes, substance abuse facility admissions, crime rates, and fatal drug overdoses (Buchmueller and Carey, 2018; Patrick et al., 2016; Dave et al., 2017; Borgschulte et al., forth.; Mallatt, 2017). The lack of consistent evidence on the effectiveness of PDMPs programs is partly explained by the fact that physicians did not generally endorse PDMPs access as a solution to the opioid crisis (Buchmueller and Carey, 2018). In some of the adopting states the proportion of physicians using the PDMPs system was very low (Poston, 2012) and more generally physicians complained about the difficulty of interpreting and using prescribing history, and about the complexity in the access to this information (Islam and McRae, 2014).

To the best of our knowledge there is no study analyzing the effects of PDMPs programs on foster care admissions. In our analysis, we distinguish the effect of operational PDMPs from the effect of programs that introduced mandatory access (Buchmueller and Carey, 2018; Dave et al., 2017; Mallatt, 2017).

2.2 Foster Care

The foster care system provides a temporary arrangement to a minor who has been placed into a ward, group home or private home of a state-certified caregiver after being removed from his legal guardians' care because of child abuse, neglect or abandonment. In 2015, over 670,000 children spent time in U.S. foster care. On average children remain in state care for nearly two years, although about 6% of children stay for five or more years. In 2016 more than 20,000 young people aged out of foster care without permanent families (US Department of Health and Human Services, 2016). From 2013 to 2015, the number of children in foster care increased by 7% according to the U.S. Department of Health and Human Services' Administration on Children and Families. In 32 percent of all foster care placements, parental substance use was cited as a reason for the removal.

The foster care caseload grew sharply from the middle 1980s through the late 1990s as fewer children were exiting care and children had longer stays in foster care (Figure 3). Foster care placements grew as a result of a growth in the reports of child maltreatment (Barbell and Freundlich, 2001) and the fact that the foster care system became an alternative to mental health and juvenile justice institutions (Landsverk and Garland, 1999). Furthermore, during that period there was also a sharp increase in parental incarceration (Swann and Sylvester, 2006) and the diffusion of crack cocaine, followed by the meth epidemic across the US (Cunningham and Finlay, 2013).

The number of children in care declined sharply in the early 2000s as a result of more and quicker exits from care. The progress in the early 2000s was linked to the implementation of laws meant to prevent children from languishing in foster care and providing financial subsidies as incentives to adopt (e.g., President Bill Clinton's signing of the Adoption and Safe Families Act in 1999, Golden (2000)).

Since 2010 the number of children in foster care has been increasing. Foster care experts and media reports suggest that this surge in foster care numbers is the result of parental drug addiction, particularly to opioids.

Previous studies have investigated the relationship between substance use and child maltreatment. Markowitz and Grossman (2000) provide evidence of a negative elasticity between child abuse and beer taxes, but only weak evidence of a relationship between cocaine use and child maltreatment. Similarly Paxson and Waldfogel (2002) do not find a significant relationship between cocaine arrest and foster care or child maltreatment. On the contrary, Cunningham and Finlay (2013) show that meth use caused foster care caseloads to increase through higher number of parental neglect and physical abuse cases. More recently, Quast et al. (2018) document a strong association between removal rates for parental neglect and opioid prescriptions in Florida. However, there is limited causal evidence on the relationship between drug abuse and child maltreatment, and no study on the effects of PDMPs on child maltreatment and foster care admissions. Our paper attempts to fill this gap in the literature.

2.3 Data

Data on foster-care cases are drawn from the Adoption and Foster Care Analysis and Reporting System (2000-2016). The Adoption and Foster Care Analysis and Reporting System (AFCARS) is a federally mandated data collection system providing case specific information on all children covered by the protections of Title IV-B/E of the Social Security Act (Section 427). The database aggregates individual information on each child in foster care and each child adopted under the authority of all state child welfare agencies. State participation became mandatory in 1998. For each child in foster-care in a given year, we have information on the date the child entered foster care for the first time and the most recent date he entered the system. Furthermore, AFCARS data contain information on the reason behind child removal (e.g., neglect, physical abuse, parental drug use, parental incarceration etc.). The foster care data files contain information on child demographics including gender, birth date, race, and ethnicity.

To construct our set of control characteristics, we collected state level controls from the Population and Housing Unit Estimates (PHUE, 2000-2016), the US Census (2000) and the American Community Survey (2001-2016). We use data from the PHUE to calculate child population. We include data on age composition, share of black population, share of Hispanic population, median income, gender composition, and unemployment rate drawn from the 2000 US Census and the 2001-2016 American Community Survey. Finally, following Meara et al. (2016), we collected data on the timing of adoption of other laws that may have affected prescription drug abuse (e.g., Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams laws, require ID laws, and tamper-resistant prescription form requirement laws).

3 Empirical Specification

To identify the dynamic response of foster care admissions to drug monitoring programs we employ an event-study methodology and estimate the following equation:

$$Child_{st} = \delta_s + \phi_t + \sum_{-3}^{3}(\gamma_t Mandate_{s,t-\tau}) + \beta X_{st} + \delta_s * t + \lambda P_{t>t+3} + \epsilon_{st} \tag{1}$$

where $Child_{st}$ is the number of new foster-care admission in year t in state s. Given the skewed distribution of foster care admissions, we use the inverse hyperbolic transformation (IHS) of foster cases as our dependent variable[2]. $Mandate_{st}$ is an indicator for whether state i has introduced a mandatory PDMPs in year t. X_{st} are a set of time-variant state level controls (age composition, share of black population, share of Hispanic population, median income, gender composition, and unemployment rate). All our estimates control for the natural logarithm of the child population (aged 0-18). δ_s are state fixed effects that capture time-invariant state level characteristics; ϕ_t are year fixed effects capturing the average national trend in child abuse; $\delta_s * t$ are state specific time trends; and $P_{t>t=3}$ is an indicator for observations after $t+3$. Standard errors are clustered at the state level. All estimates are weighted by child population. This model isolates the short-run impact of the policy.

Dave et al. (2017) show that adopters of mandatory access provisions were very similar to states having a PDMP but without mandatory provisions. For this reason, to investigate the role of mandatory access PDMPs, we restrict the analysis to states with an operational PDMPs. The underlying assumption is that the states that had an operational PDMPs but did not introduce a mandatory access provision provide a valid counterfactual for treated states (states with mandatory access provisions).

We then investigate the effects of PDMPs and mandatory PDMPs in a standard difference-in-difference specification. Thus, our identification strategy relies on the assumption that

[2] In the Appendix, we show that results tend in the same direction when using the number of cases or the number of cases per 1,000 individuals as alternative scales

prior to the adoption of drug monitoring programs treated and untreated states were following parallel trends and in the absence of programs' implementation their path would have not been affected. To identify the effects of the program, we exploit within-state changes in trends at the timing of implementation of drug monitoring programs. Consistent with the evidence from previous work on the effects of PDMPs on drug abuse (Buchmueller and Carey, 2018; Dave et al., 2017) and based on the dynamic response found in our event study that show the effect of mandatory PDMPs materializes two years after the enactment, we use a two-year lag to estimate our difference-in-difference model. The lagged effect is explained by the fact that it takes time for provider practices to diffuse across the state and there is a natural lag between increased prescription drug monitoring and the reduction in the overall supply of drugs. Similarly to Kolstad and Kowalski (2012) we also preset results defining pre, during (t to t+1), and post (t+2 and on).

In practice, we estimate the following OLS model

$$Child_{st} = \alpha + \beta Mandate_{s,t+2} + \psi X_{st} + s_s + \gamma_t + \epsilon_{st} \tag{2}$$

where $Child_{st}$ is the number of abuses or foster-care admissions in year (or month) t in state i. $Mandate_{s,t+2}$ is an indicator for whether state s has introduced a mandatory Prescription Drug Monitoring Program by year t. X_{st} are a set of time-variant state level controls (age composition, share of black population, share of Hispanic population, median income, gender composition, and unemployment rate). All our estimates control for the natural logarithm of the child population (aged 0-18). Following Meara et al. (2016), we control for the adoption of other laws that may have affected prescription drug abuse (e.g., Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams laws, require ID laws, and tamper-resistant prescription form requirement laws). Finally, we include year fixed effects, capturing the average national trend in child abuse, state fixed effects that capture time-invariant county level characteristics, and state specific time trends. All estimates are weighted by child population.

4 Main Results

4.1 Trends and Descriptive Statistics

We report descriptive statistics from the foster care data in Table 2. Females constitute 48% of our sample, African-Americans are over-represented in the sample (29%), and Hispanics make up 21% of the total foster care population. The average age of the representative child in our sample is 7.4. 80% of the children have been removed only once, 15% of the children twice, and the remaining 5% more than twice. For each removal, child welfare workers can report more than one reason and thus the route of admission can add up to more than one. The most common reasons for child removals are child neglect (53%), drug abuse (24%), caretaker inability to cope (17%), child behavioral problem (16%), physical abuse (15%), inadequate housing (9%), and parental incarceration(7%).

To identify the effects of PDMPs and Mandatory PDMPs on foster care admissions, we calculated the number of foster-care cases by year and state. Table 3 reports the average number of cases by state and year for our main outcomes of interest. There were approximately 4,500 child removals in a state-year. Over the last few years there has been a sharp increase in the number of child removals. The share of removals associated with parental drug abuse rose from 22% in 2000 to 39% in 2015. This trend closely mirrors the increase in fatal overdoses (Figure 1) and is largely driven by the increase in the cases associated with child neglect or caregiver drug-abuse (Figure 2). These figures parallel the dramatic surge in the distribution of prescription drugs across the US (Figure 4).

Although many state officials and several state reports suggest the surge in foster care cases is a direct result of the drug epidemic, it is difficult to clearly identify how many children are removed from their homes because of parent's substance use as there is no standard for how states report substance use and child neglect.[3] Furthermore, several states changed the law to allow child welfare authorities to intervene and pull children out of homes where parents are addicted. For instance, in some states the law now defines a parent's opioid abuse as child neglect with the goal to facilitate the intervention authorities. It is also worth noting that the majority of identified drug-abuse cases (60%) are also classified as cases of child neglect. For this reason and given the inconsistency across states in the measurement of substance use in foster-care data, in the main analysis we focus on the number of removals, cases of child neglect and cases of physical abuse.[4]

Consistent with the new federal laws requiring hospitals to notify child protective services of any infants affected by prenatal substance exposure (Patrick et al., 2017), we find that the average age for a child in foster care went down significantly over the period studied (Figure 5), with the median age going down from 8 in the early 2000s to 6 since 2010.

4.2 PDMPs and Foster Care Admissions

In Figures 6-7, we explore the dynamic response of child removals to the adoption of operational, and then mandatory PDMPs. The event-study analysis shows that there was no significant effect of PDMPs on child removals (Figure 6). In contrast, following the adoption of mandatory PDMPs we observe a marked decline in the number of child removals (Figure 7).[5]

Figure 7 provides evidence supporting the parallel trend assumption. Adopting and non-adopting states with an operational PDMPs were on similar trend paths before the introduction of the mandatory PDMPs. This evidence supports a causal interpretation of our finding, mitigating the concern that the timing of a mandatory PDMP adoption may be

[3] http://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2016/10/07/drug-addiction-epidemic-creates-crisis-in-foster-care.

[4] See also the Children's Bureau Express Report: https://cbexpress.acf.hhs.gov/index.cfm?event=website.viewArticles&issueid=181&articleid=4855.

[5] As mentioned above, this result is consistent with the evidence on the effects of PDMPs on drug abuse Buchmueller and Carey (2018); Dave et al. (2017), but it also relates to recent findings on the impact of medical marijuana laws suggesting that the effectiveness of the laws in reducing overdose death rates crucially depends on the regulation of dispensaries (Powell et al., 2018).

endogenous to unobserved determinants of foster care admissions. The event-study highlights that the effects of the policy are not immediate. The effect of the mandate becomes significant two years after its adoption. As mentioned above, the lagged effect is explained by the fact that it may take time before providers can find representative information for any patient (Buchmueller and Carey, 2018), and for the practices to diffuse within a state. This dynamic may also reflect the lag between reduced doctor shopping, the diversion of prescription drugs, and the fact that drug abusers may have access to alternative supply sources in the short run (Dave et al., 2017).

Given the dynamic of the effects visualized by the event-study analysis, our difference-in-difference strategy focuses on the effect of mandatory PDMPs two years after the implementation of the program. However, we report alternative definitions of the model considering separately pre (before t), during (t to $t+1$), and post ($t+2$ and onwards) in the robustness checks. Table 4 presents the estimated effect of PDMPs on the number of children in foster care by main reason of removal. Consistent with both Buchmueller and Carey (2018) and Dave et al. (2017), we find no evidence of a significant effect of PDMPs on child removals. However, mandatory PDMPs had a significant effect on removals reducing both cases associated with neglect and physical abuse (Table 5).

The magnitude of the effect is economically significant. The introduction of mandatory procedures reduced child removals by 8%. Our results appear consistent with recent estimates of the effects of mandatory PDMPs on drug abuse. Dave et al. (2017) estimate that the adoption of mandatory access provision reduced treatment admissions related to Rx drugs by 32% among individuals aged 18 to 24, by 17% among the 25-44 years old, and by 12% among the over 45. Using aggregated claims data from Medicare's prescription drug program (Medicare Part D), Buchmueller and Carey (2018) find that must access PDMP led to a 8 % fall in the share of individuals obtaining opioids from five or more prescribers, 16 percent decline for five or more pharmacies, and a 14% decline in opioid takers' number of new patient visits. Consistent with the evidence of larger effects among younger individuals

(Dave et al., 2017), we find that the magnitude of the effect of mandatory PDMPs on child removals are strongest among children of young adults and decrease with caregivers' age. Mandatory procedures reduced child removals by 14% among children whose first caregiver was aged 18 to 24; 10% for children of individuals aged between 25 and 44; and 4% among children of over 45 years old (Figure A.2 and Table A.1).

Our results are driven by first removals (see Figure A.3), while there is no evidence of a significant effect on repeated removals (see Figure A.4). In states that did not adopted the mandatory PDMP, removals continued to increase, in adopting states we observe a slight decrease in the number of removals (Figure A.5). Breaking up the results by family structure, we find that the effect is driven by children of single or unmarried parents, while there is no evidence of a significant impact among children of married couples (Figure A.6).

Foster-care cases associated with neglect and physical abuse were reduced by respectively 9% and 10%. These results imply a reduction of 467 removals per year or 0.27 fewer cases per 1000 children (Tables A.2-A.3, Panel A and B). We also analyze the heterogeneity of the effects across different sub-samples. While we have limited information on the socioeconomic status of the parents, we do have information on race and age of the children to conduct separate analysis by race and age. We don not find significant effects among Blacks (Table A.4). Although the coefficient is not statistically different from that for white children. The effect is larger among children aged 0-12 (Table A.5).

In sum, our baseline findings suggest that mandatory PDMPs may substantially reduce the costs associated with child removals. According to previous estimates, the fiscal costs of a child in foster care is approximately \$20,000 per year. Using this estimated cost and our results, with a back of the envelope calculation, we calculated that mandatory PDMPs reduced costs associated with child removals by approximately 476 million dollars per year, or \$4.76 billion in a decade. It is worth noting that this number does not include the long-run effects that child neglect and maltreatment may have on child health and human capital (Doyle Jr, 2007, 2008; Currie and Spatz Widom, 2010; Dube et al., 2003).

4.3 Robustness Checks

Table A.6 illustrates the sensitivity of our main results to state-level time-varying controls and state specific time trends. While including state-level controls reduces the magnitude of the coefficient, the coefficient remains negative, and statistically and economically significant. Using the method proposed by Oster (2017), we estimate that to explain away our main result on child removals the extent of selection on unobservables should be at least 14 times larger than the extent of selection on observables.

In Table A.7, we report the coefficients of a model defining pre, during (t to $t+1$), and post ($t > t+1$) implementation of the mandatory PDMP. Consistent with the event study, the estimates reveal that the effect of the Mandate materializes two years after the adoption of the mandate.

These findings are not sensitive to the inclusion of controls for whether the neighboring states had PDMPs or mandatory PDMPs accounting for potential cross-border effects (Panel A, Table A.8 and A.9). Furthermore, our results are not changed when reporting unweighted estimates (Panel B) or when excluding state-month cells with zero foster-care admissions (Panel C).

We also test the robustness of our findings to dropping one state at a time from our sample. Figure A.1 shows that the point-estimates of the effect of mandatory PDMPs on child removals are not significantly affected when a state is excluded from the analysis.[6]

Finally, one could be concerned the number of foster care admissions may be directly affected by the size of Child Protection Services staff (e.g., screen, intake, investigators, and access workers), which could be correlated with changes in the policy at the state level. To address this concern we collected data from the National Child Abuse and Neglect Data System (NCANDS) Agency File. It is worth noting that these data are not available for all states and throughout the entire period of our main analysis. However, reassuringly we find no significant relationship between the adoption of a mandatory PDMPs and the

[6]Restricting the analysis to states with a PDMP yields similar results.

number of CPS staffing (Figure A.7) nor our results are affected when including the number of investigators as an additional control in our main estimates (Table A.10).

5 Conclusion

The recent opioid epidemic has dramatic implications for the children of opioid-dependent parents. As the opioid crisis spreads to urban counties and to different groups of the population, more children are at higher risk of neglect, abuse or removal from their parental caregiver.

Many states responded to the opioid epidemic introducing Prescription Drug Monitoring Programs, electronic databases tracking a patient's prescription history. While in most states provider access and database queries are voluntary, since 2007 some states mandated prescribers and/or dispensers to query the PDMP prior to prescribing or dispensing a controlled substance. Recent studies document limited effects of operational PDMPs on drug abuse, while mandatory PDMPs were more effective Buchmueller and Carey (2018); Dave et al. (2017). Our paper contributes to the literature on the effectiveness of drug monitoring programs. We provide evidence that while operational PDMPs had no significant effects on foster care enrollments, mandatory PDMPs substantially reduced cases of child removals (-10%) with significant reductions in the number of cases associated with neglect and physical abuse. The magnitude of the effects is consistent with previous estimates of the effects of mandatory PDMPs on drug abuse (Buchmueller and Carey, 2018; Dave et al., 2017). Effects are strongest among children of young adults (ages 18-24).

Given the evidence on the long-lasting effects of child maltreatment and foster care, the human capital, health and economic cost of the opioid crisis may be very large. The effectiveness of programs monitoring drug-prescription supports the implementation of supply-side policies aimed at reducing the diffusion of opioid substances in the population. The indirect effects of these policies on child well-being may not be negligible.

This study contributes to our understanding of the connection between parental drug use and child maltreatment, as well as the efficacy of policies on opioid abuse more generally. Both of these questions are of incredible importance. The opioid epidemic has been recognized as a national emergency. Our findings suggest that money spent on prescription drug monitoring programs would not only reduce potentially spending on opioid treatment, but it may be also partially offset by reductions in spending on foster care admissions. Policy makers should take into account the human and financial costs of parental drug abuse when evaluating policy effectiveness and allocating resources across programs aimed at contrasting the opioid epidemic.

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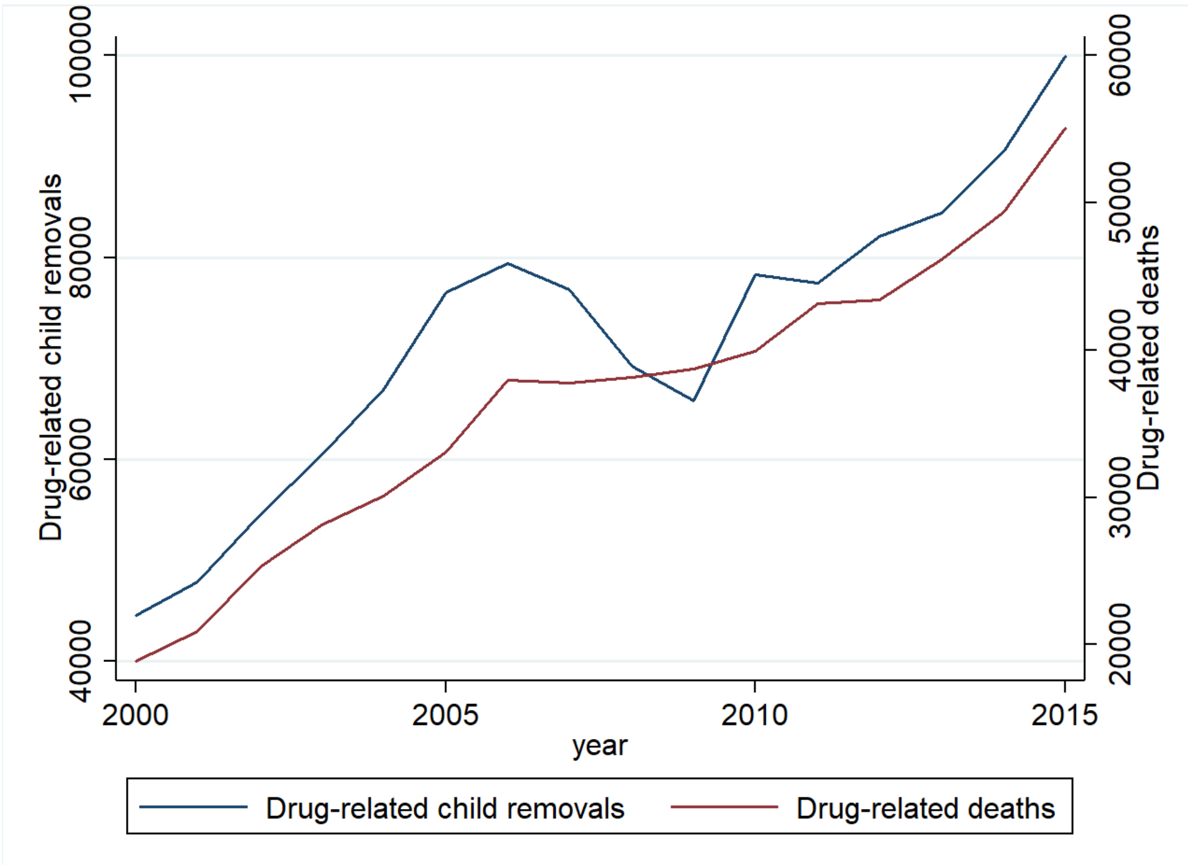
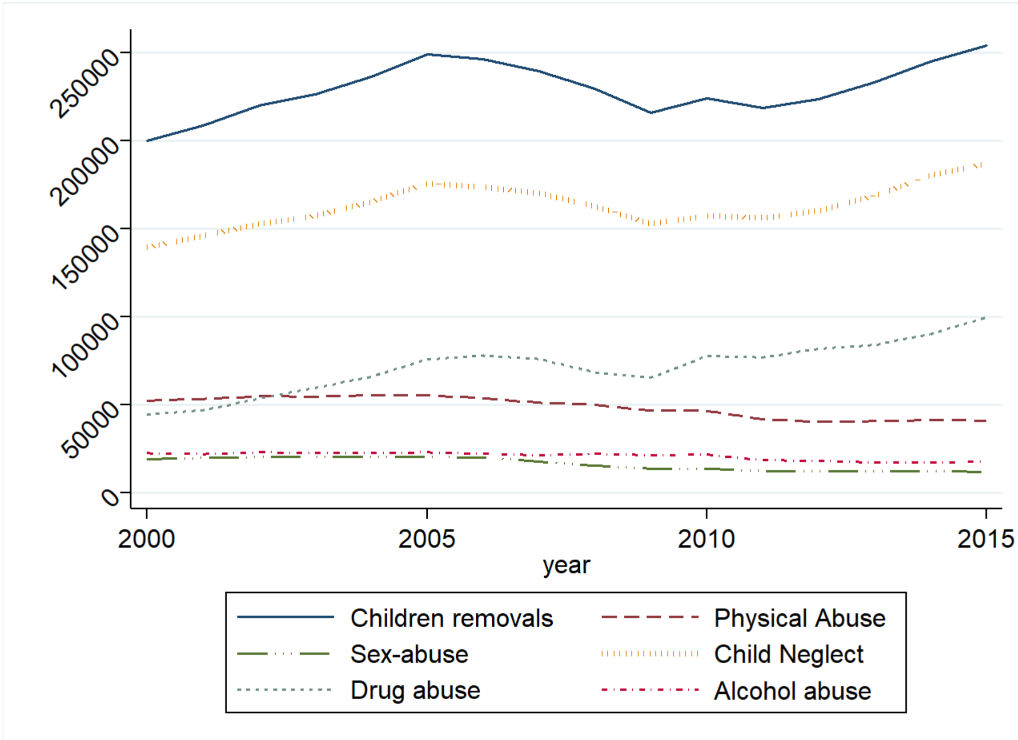
Figures and Tables

Figure 1: Trends in Drug Related Deaths (2000-2015, CDC) and Drug-Related Foster Child Removals



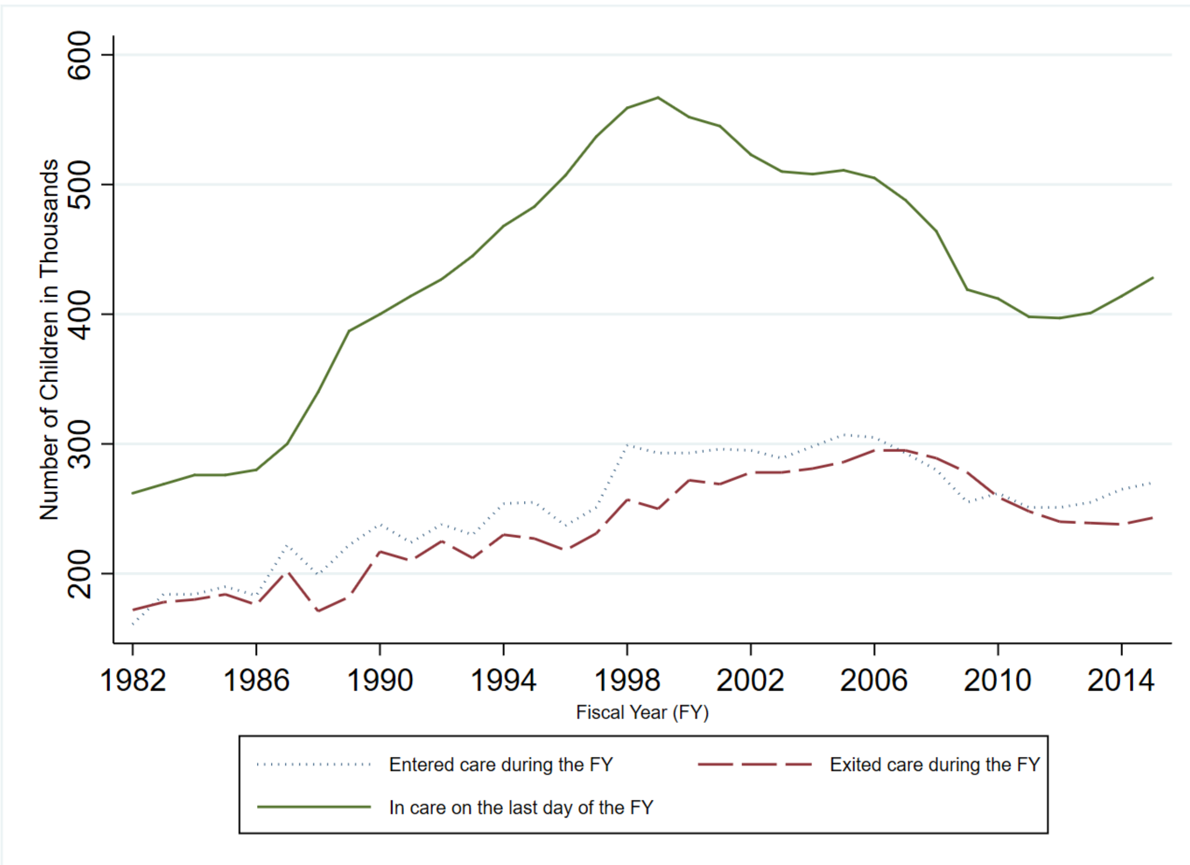
Notes - Data on drug-related deaths are drawn from CDC database on detailed mortality causes. The Underlying Cause of Death database contains mortality and population counts for all U.S. counties. Data are based on death certificates for U.S. residents. Each death certificate identifies a single underlying cause of death and demographic data. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2015).

Figure 2: Trends in Child Removals



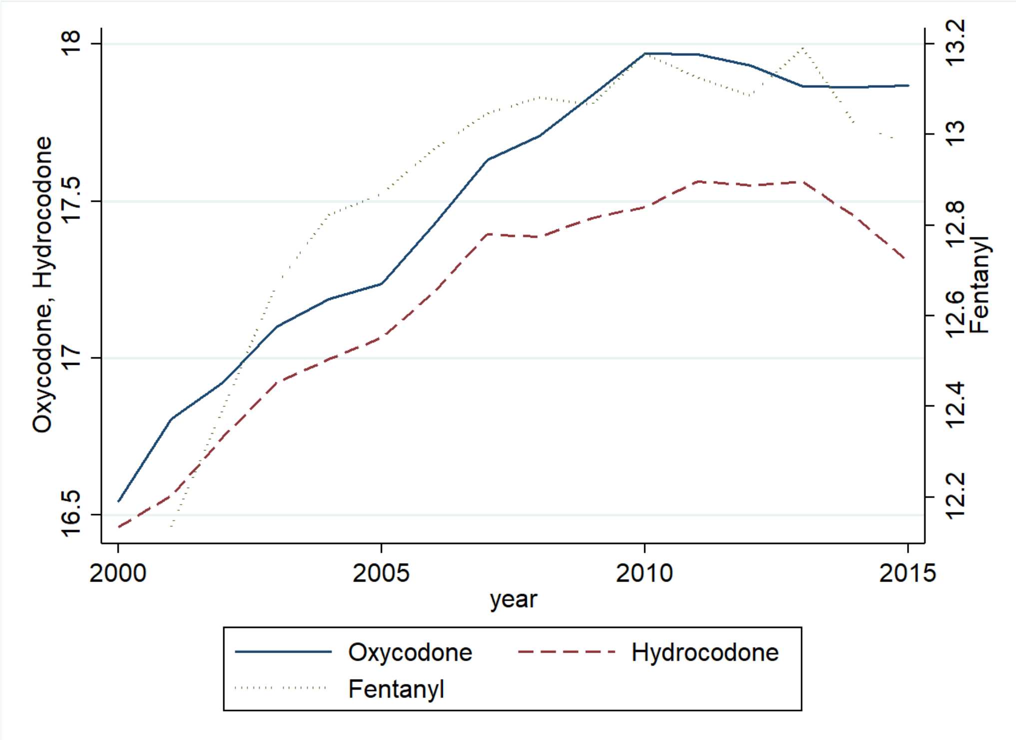
Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2015).

Figure 3: Trends in Foster Care Use, FY1982-FY2015



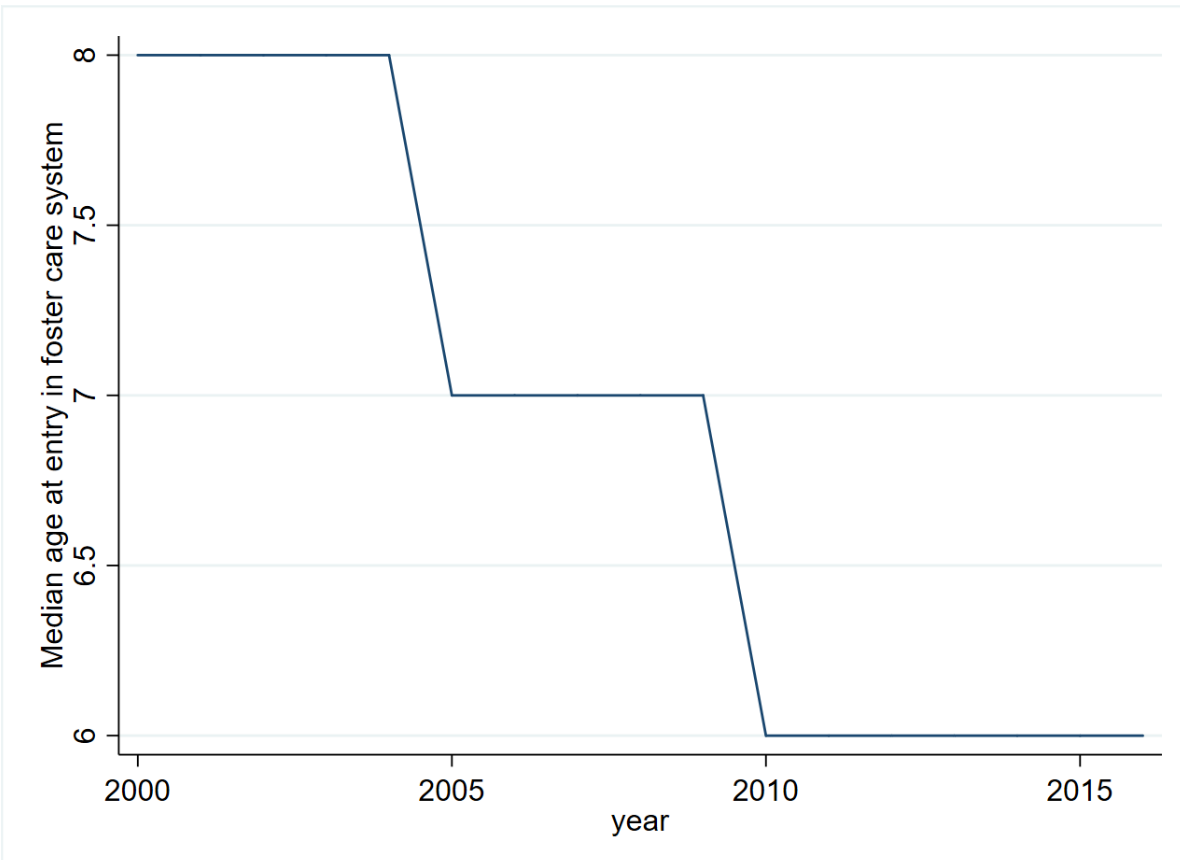
Notes - Source: Table updated by the Congressional Research Service on December 1, 2016 for the 2016 version of the House Ways and Means Committee Green Book. All data were rounded to the nearest thousand for display. However, whenever more precise data were available, those data were used to calculate the rates shown.

Figure 4: Retail Drug Distribution by Drug Code for U.S.



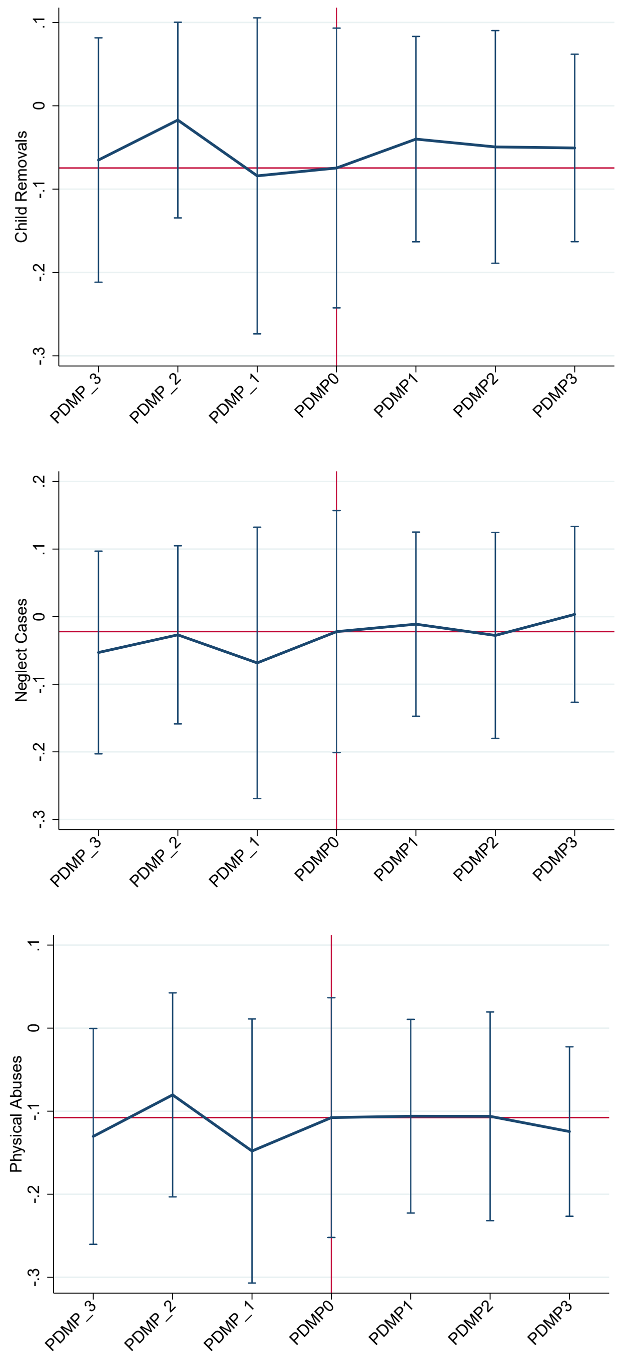
Notes - Data are drawn from the Automated Reports and Consolidated Ordering System (ARCOS) provided by the U.S. Department of Justice Drug Enforcement Administration, Diversion Control Division. Data cover the period 1999-2015.

Figure 5: Median age at the latest entry in the foster care system



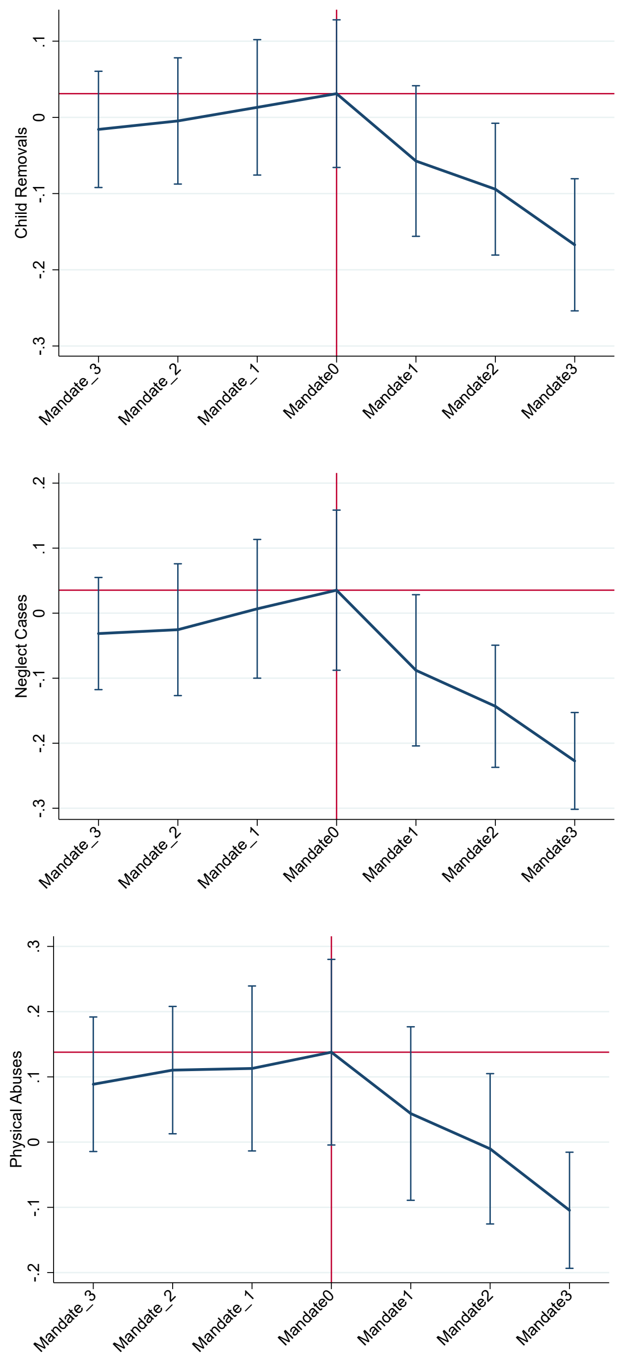
Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016).

Figure 6: Effect of PDMPs Study-Child Removal



Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). 90% level confidence interval are reported in parenthesis.

Figure 7: Effect of mandatory PDMP on Child Removals



Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). 90% level confidence interval are reported in parenthesis.

Table 1: Effective Dates of Electronic PDMPs and Mandates

State	PDMP		Mandate	
Alaska	January	2012		
Alabama	August	2007		
Arkansas	March	2013		
Arizona	December	2008		
California	July	2009		
Colorado	February	2008		
Connecticut	July	2008		
Delaware	August	2012	March	2012
Florida	October	2011		
Georgia	July	2013		
Hawaii	January	1982		
Iowa	March	2009		
Idaho	July	2008		
Illinois	Janurary	2008		
Indiana	July	2008		
Kansas	April	2011		
Kentucky	March	2005	July	2012
Louisiana	January	2009	August	2014
Massachusetts	December	2010	June	2013
Maryland	January	2014		
Maine	January	2005		
Michigan	March	2011		
Minnesota	April	2010		
Missouri	July	2017		
Mississippi	March	2011	September	2011
Montana	October	2012		
North Carolina	October	2008		
North Dakota	January	2007		
Nebraska	April	2011		
New Hampshire	October	2014		
New Jersey	January	2012		
New Mexico	August	2005	September	2012
Nevada	October	2004	October	2007
New York	August	2013	August	2013
Ohio	October	2006	November	2011
Oklahoma	July	2006		
Oregon	September	2011		
Pennsylvania	August	2016		
Rhode Island	September	2012		
South Carolina	June	2008		
South Dakota	March	2012		
Tennessee	December	2006	January	2013
Texas	August	2012		
Utah	January	2006		
Virginia	June	2006		
Vermont	April	2009	November	2013
Washington	January	2012		
Wisconsin	May	2013		
West Virginia	January	2004	June	2012
Wyoming	July	2004		

Notes - Dates obtained from the National Alliance for Model State Drug Laws, Brandeis University's Prescription Drug 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.

Table 2: Foster Care Selected Descriptive Statistics, Adoption and Foster Care Analysis and Reporting System (AFCARS), 2000-2016

	Mean	S.d.
Child characteristics		
White	0.61	0.49
Black	0.29	0.45
Hispanic	0.21	0.41
Age at first entry in foster care	7.04	5.95
Age at latest entry	7.46	5.87
# times removed	1.27	0.68
Route of most recent removal		
Child neglect	0.53	0.50
Physical abuse	0.36	0.00
Drug abuse	0.24	0.43
Caretaker inability to cope	0.17	0.38
Child behavior	0.17	0.37
Inadequate housing	0.09	0.29
Parent incarcerated	0.07	0.25
Alcohol abuse	0.07	0.25
Sexual abuse	0.05	0.22
Abandon	0.05	0.21
Total Number of Cases	5,192,037	

Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). The table reports unweighted summary statistics by state and year for the main outcome variables in all US states. Data spans years 2000 to 2016.

Table 3: Summary Statistics by State and Year, AFCARS (2000-2016)

	Mean	Standard deviation
# removals	4519.496	5190.235
Reason:		
Neglect	3214.062	4151.742
Drug abuse	1432.445	1902.54
Physical abuse	960.282	1313.524
Alcohol abuse	419.026	539.051
Sexual abuse	321.487	474.670

Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). The table reports unweighted summary statistics by state and year for the main outcome variables in all US states. Data spans years 2000 to 2016.

Table 4: Effects of PDMP on Foster Cases (IHS)

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
$PDMP_{t+2}$	-0.218	-0.205	-0.181
	(0.173)	(0.176)	(0.125)
Observations	867	867	867
Mean of Dep. Var.	8.531	8.156	6.855
Std.Dev. of Dep. Var.	1.448	1.422	1.400

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant prescription form requirement. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

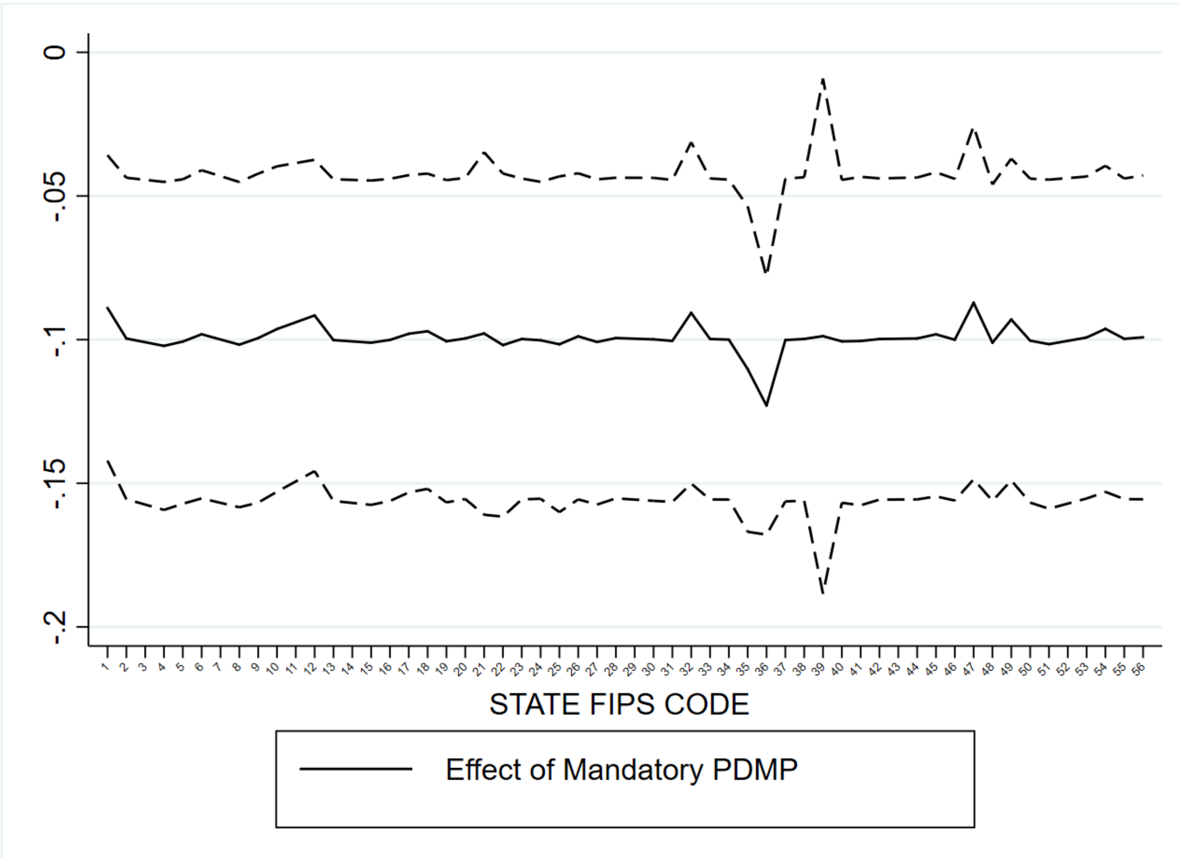
Table 5: Effects of Mandatory PDMPs on Foster Cases (IHS)

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
Mandate $_{t+2}$	-0.078**	-0.100***	-0.089**
	(0.034)	(0.034)	(0.043)
Observations	371	371	371
Mean of Dep. Var.	8.711	8.338	6.890
Std.Dev. of Dep. Var.	0.908	0.967	0.973

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant prescription form requirement. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

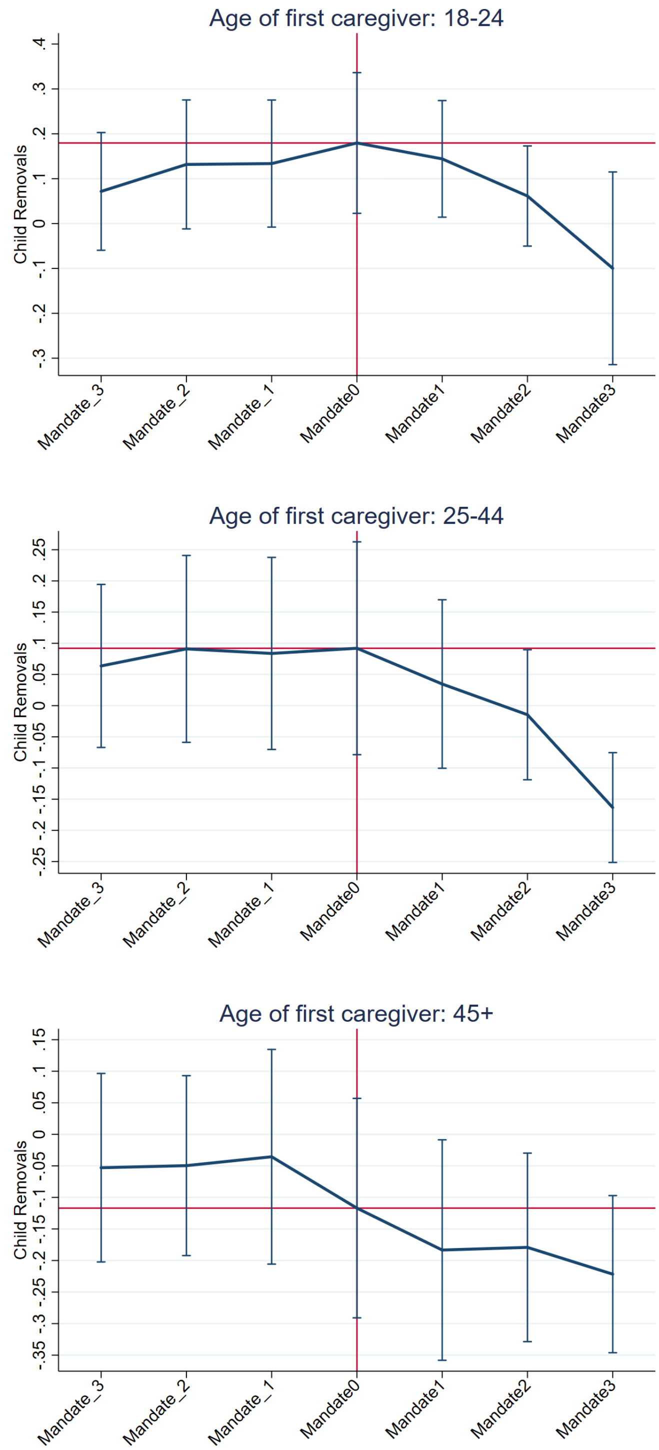
Appendix

Figure A.1: Sensitivity to Exclusion of a Single State from the Sample



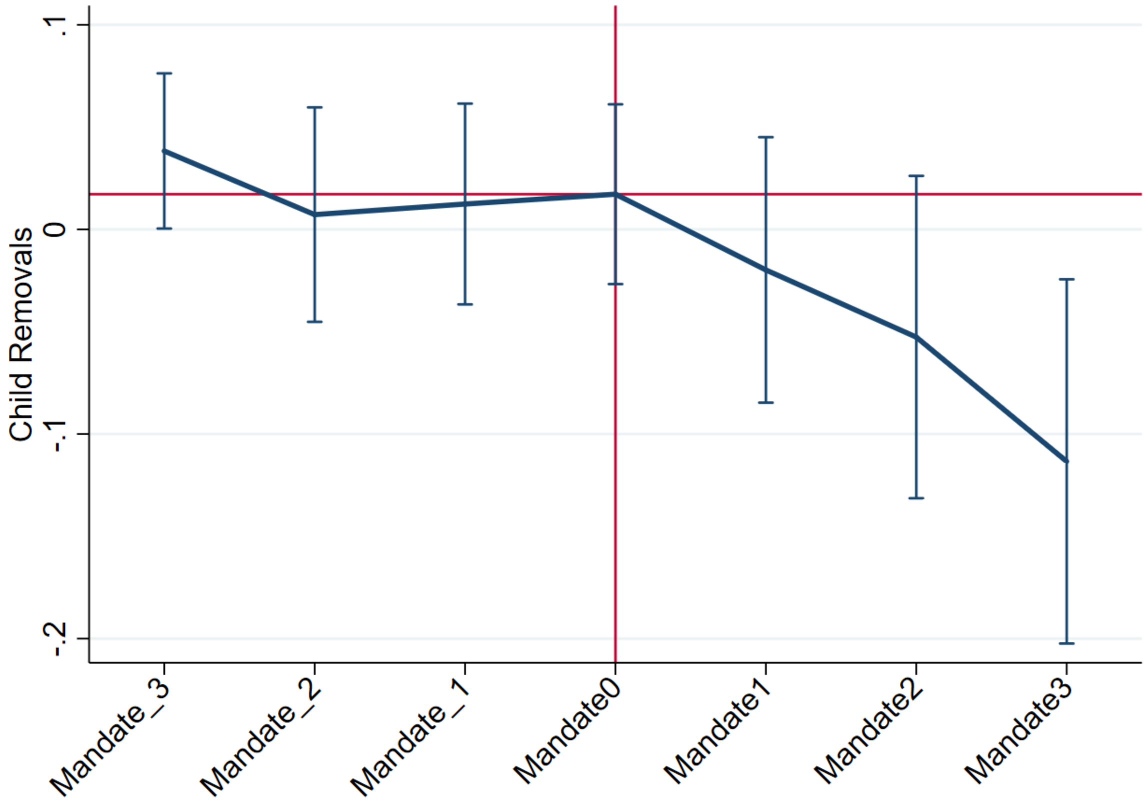
Notes - The figure illustrate the sensitivity of the coefficient of mandatory PDMPs on cases of child removals to dropping one state at a time from our main regression. The dependent variable is the inverse hyperbolic transformation of child removals occurred in each state in a given year between 2000 and 2016. Dashed lines represent the 90% level confidence intervals.

Figure A.2: Effect of mandatory PDMP on First Removals, by Age of First Caregiver



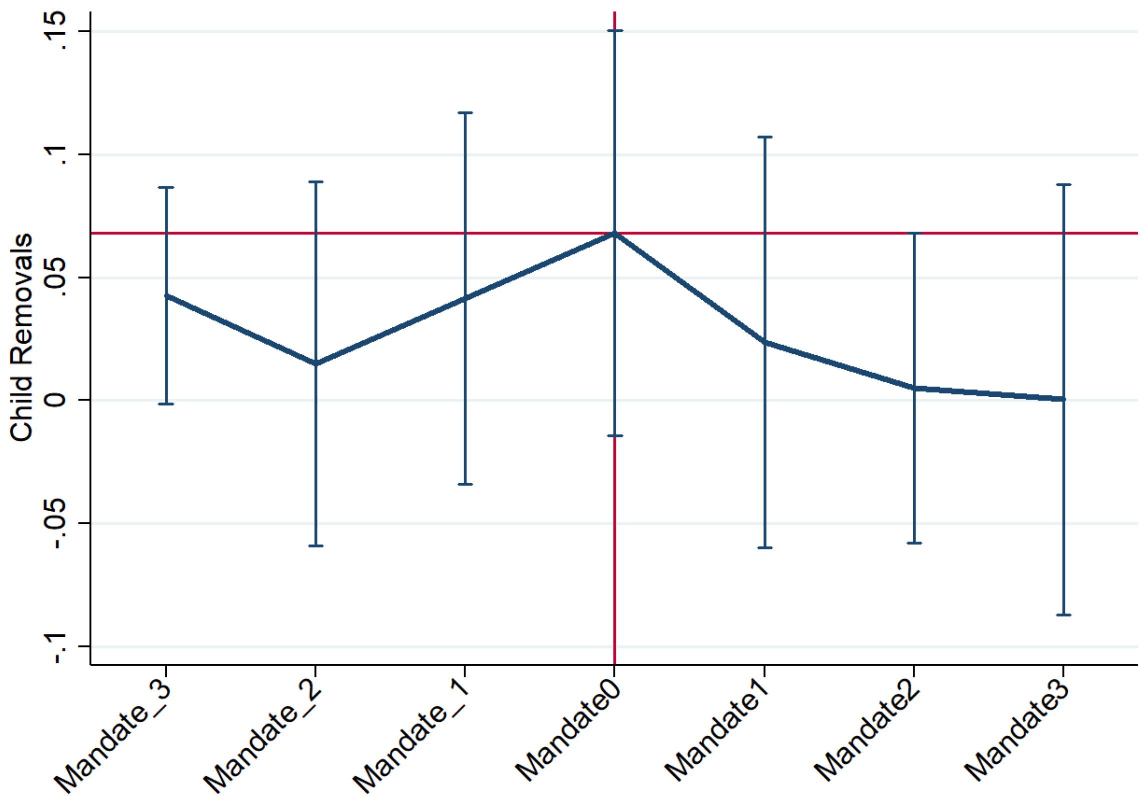
Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data are drawn from the National Child Abuse and Neglect Data System (NCANDS) Agency File agency file (2000-2016). 90% level confidence interval are reported in parenthesis.

Figure A.3: Effect of mandatory PDMP on First Removals



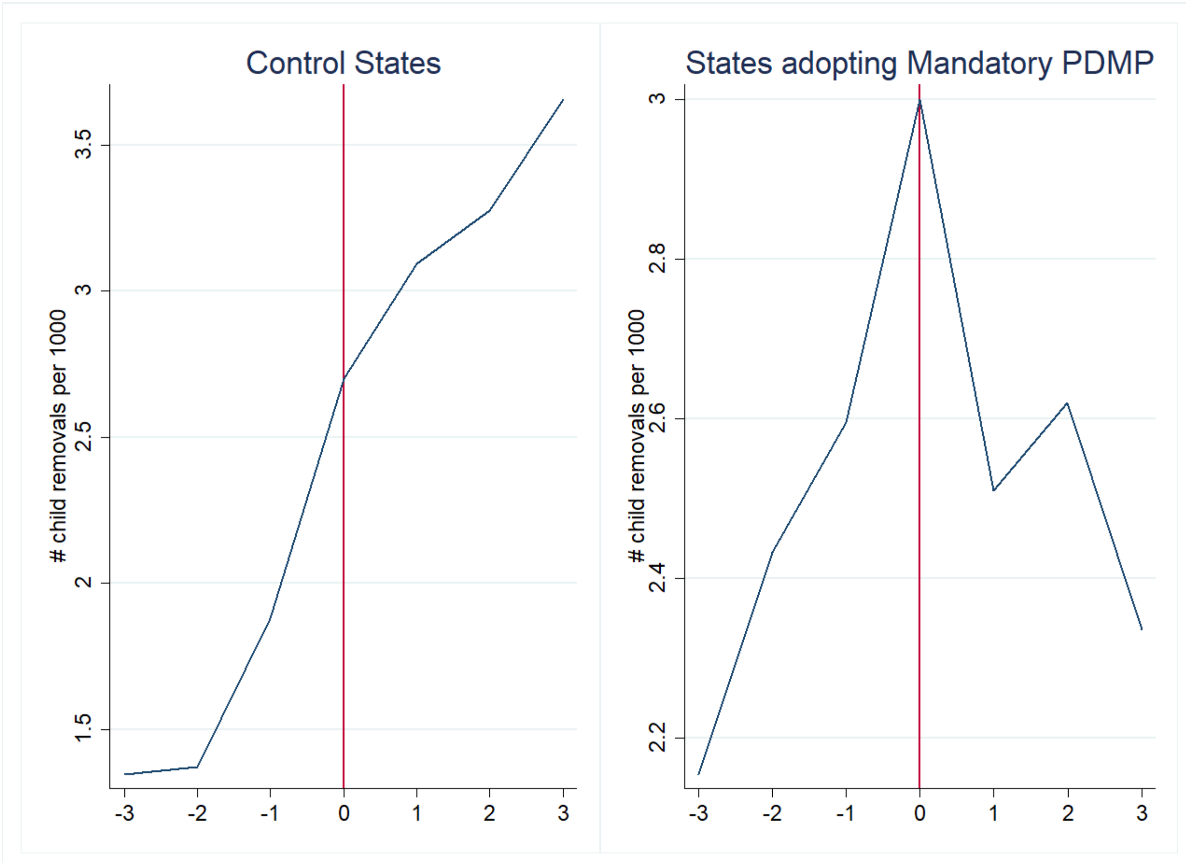
Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data are drawn from the National Child Abuse and Neglect Data System (NCANDS) Agency File agency file (2000-2016). 90% level confidence interval are reported in parenthesis.

Figure A.4: Effect of mandatory PDMP on Repeated Removals



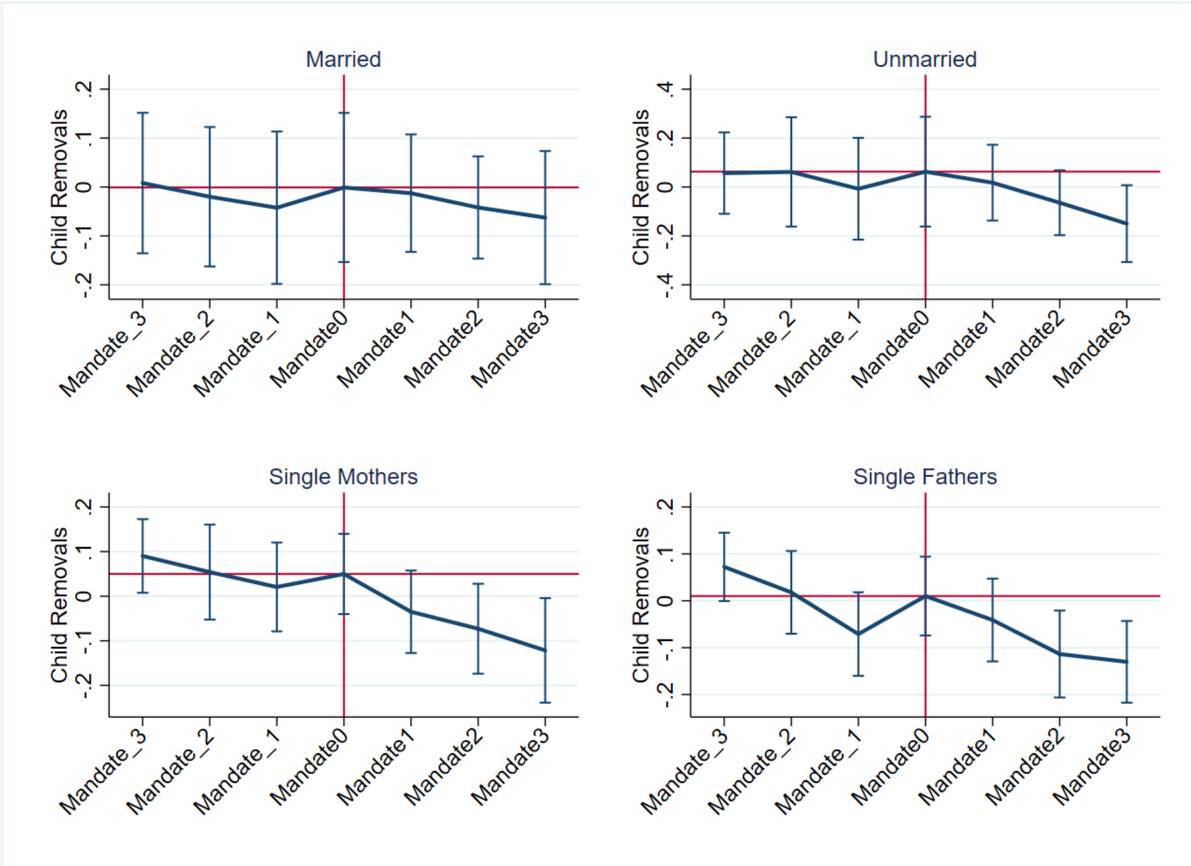
Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data are drawn from the National Child Abuse and Neglect Data System (NCANDS) Agency File agency file (2000-2016). 90% level confidence interval are reported in parenthesis.

Figure A.5: Effect of mandatory PDMP on # of child removals



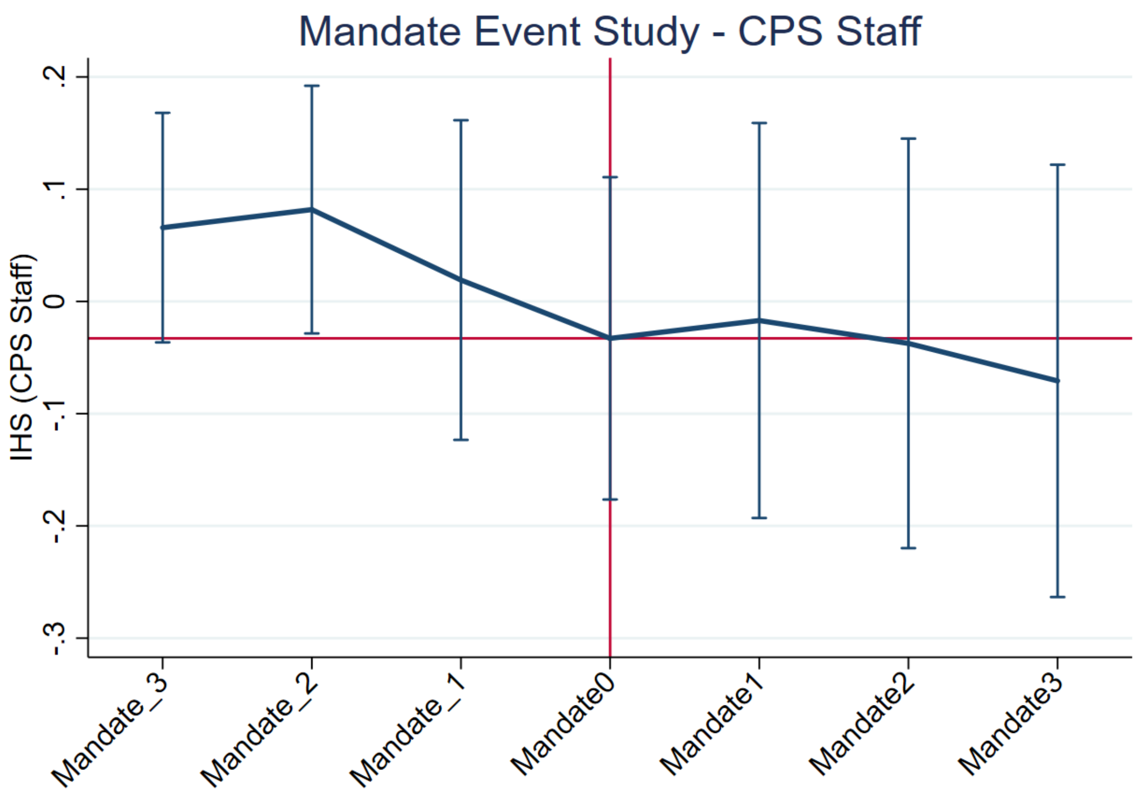
Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). For the control states we set 2012 as 0, as this is the year most states adopted the mandatory PDMP.

Figure A.6: Effect of mandatory PDMP on # of child removals, by family type



Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). For the control states we set 2012 as 0, as this is the year most states adopted the mandatory PDMP.

Figure A.7: Effect of mandatory PDMP on CPS Staff



Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, black, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). 90% level confidence interval are reported in parenthesis.

Table A.1: Effects of Mandatory PDMPs on Foster Cases (Age of First Caregiver)

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
<u>Age of first caregiver: 18-24</u>			
Mandate$_{t+2}$	-0.140*	-0.155***	-0.182***
	(0.075)	(0.052)	(0.064
Observations	371	371	371
Mean of Dep. Var.	6.738	6.392	4.909
Std.Dev. of Dep. Var.	0.956	0.991	1.137
<u>Age of first caregiver: 25-44</u>			
Mandate$_{t+2}$	-0.100**	-0.123**	-0.110*
	(0.042)	(0.047)	(0.062)
Observations	371	371	371
Mean of Dep. Var.	8.248	7.977	6.511
Std.Dev. of Dep. Var.	1.133	0.969	0.970
<u>Age of first caregiver: 45+</u>			
Mandate$_{t+2}$	-0.037	-0.057	-0.031
	(0.046)	(0.058)	(0.096)
Mean of Dep. Var.	6.544	6.172	4.854
Std.Dev. of Dep. Var.	1.346	1.202	1.157

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.2: Effects of PDMPs on Foster Cases

	(1) removals	(2) neglect cases	(3) physical abuses
Number of cases			
$PDMP_{t+2}$	-348.367*	-241.950	-125.614**
	(182.852)	(178.239)	(59.854)
Observations	867	867	867
Mean of Dep. Var.	4543	3235	945.9
Std.Dev. of Dep. Var.	5247	4231	1307
Cases per 1000 children			
$PDMP_{t+2}$	-0.017	0.005	-0.021
	(0.063)	(0.058)	(0.020)
Observations	867	867	867
Mean of Dep. Var.	3.280	2.301	0.651
Std.Dev. of Dep. Var.	1.473	1.170	0.482

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.3: Effects of Mandatory PDMP on Foster Cases

	(1) removals	(2) neglect cases	(3) physical abuses
Number of cases			
Mandate$_{t+2}$	-467.742**	-394.359**	-92.921***
	(181.931)	(182.734)	(27.222)
Observations	371	371	371
Mean of Dep. Var.	4563	3407	775.8
Std.Dev. of Dep. Var.	5105	4517	982
Cases per 1000 children			
Mandate$_{t+2}$	-0.276**	-0.202**	-0.049***
	(0.125)	(0.081)	(0.016)
Observations	371	371	371
Mean of Dep. Var.	3.556	2.541	0.598
Std.Dev. of Dep. Var.	1.554	1.306	0.317

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.4: Effects of Mandatory PDMPs on Foster Cases (Races)

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
<u>Whites</u>			
Mandate$_{t+2}$	-0.040	-0.057*	-0.056
	(0.039)	(0.030)	(0.050)
Observations	371	371	371
Mean of Dep. Var.	9.060	8.706	7.175
Std.Dev. of Dep. Var.	0.911	0.962	0.960
<u>Blacks</u>			
Mandate$_{t+2}$	-0.024	-0.031	-0.086
	(0.055)	(0.053)	(0.067)
Observations	371	371	371
Mean of Dep. Var.	7.726	7.396	6.038
Std.Dev. of Dep. Var.	1.602	1.621	1.690

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.5: Effects of Mandatory PDMPs on Foster Cases (Age groups)

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
Age 0-6			
Mandate_{t+2}	-0.078**	-0.099***	-0.096*
	(0.038)	(0.035)	(0.051)
Observations	371	371	371
R-squared	0.996	0.994	0.993
Mean of Dep. Var.	8.169	7.810	6.218
Std.Dev. of Dep. Var.	0.926	0.974	1.026
Age 7-12			
Mandate_{t+2}	-0.093**	-0.115***	-0.071
	(0.038)	(0.039)	(0.043)
Observations	371	371	371
Mean of Dep. Var.	7.296	6.920	5.559
Std.Dev. of Dep. Var.	0.912	0.972	0.968
Age 13-18			
Mandate_{t+2}	-0.068*	-0.089*	-0.119*
	(0.036)	(0.048)	(0.061)
Observations	371	371	371
Mean of Dep. Var.	6.928	6.500	5.324
Std.Dev. of Dep. Var.	0.904	1.006	0.941

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.6: Mandatory PDMPs and Foster Care Admissions

	(1)	(2)	(3)	(4)
	Child removals			
Mandate$_{t+2}$	-587.285*	-446.528	-611.210**	-463.499**
	(303.077)	(275.098)	(290.749)	(183.450)
Observations	371	371	371	371
Mean of Dep. Var.	4563	4563	4563	4563
Std.Dev. of Dep. Var.	5105	5105	5105	5105
	Child removal cases associated with neglect			
Mandate$_{t+2}$	-850.913**	-509.274*	-616.379*	-390.716**
	(341.638)	(293.915)	(313.831)	(184.450)
Observations	371	371	371	371
Mean of Dep. Var.	3407	3407	3407	3407
Std.Dev. of Dep. Var.	4517	4517	4517	4517
	Child removal cases associated with Physical Abuse			
Mandate$_{t+2}$	106.755	-15.254	-31.471	-92.894***
	(92.016)	(53.570)	(71.080)	(27.333)
Observations	371	371	371	371
Mean of Dep. Var.	775.8	775.8	775.8	775.8
Std.Dev. of Dep. Var.	982	982	982	982
State F.E.	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES
Time-varying state-levelc controls	NO	YES	YES	YES
Other laws	NO	NO	YES	YES
State specific time trends	NO	NO	NO	YES

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant prescription form requirement. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.7: Effects of Mandatory PDMPs on Foster Cases (IHS), Alternative Model

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
during $(t - t + 1)$	0.001	0.003	0.013
	-0.028	-0.032	-0.034
after $(t > t + 1)$	-0.078**	-0.098**	-0.082*
	-0.037	-0.038	-0.045
Observations	371	371	371
Mean of Dep. Var.	8.711	8.338	6.890
Std.Dev. of Dep. Var.	0.908	0.967	0.973

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant prescription form requirement. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.8: Effects of PDMPs on Foster Cases

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
Control for border effects			
PDMP$_{t+2}$	-0.224	-0.211	-0.186
	(0.175)	(0.179)	(0.127)
Border PDMP$_{t+2}$	-0.103	-0.109	-0.086
	(0.080)	(0.082)	(0.065)
Observations	867	867	867
R-squared	0.902	0.902	0.924
Mean of Dep. Var.	8.531	8.156	6.855
Std.Dev. of Dep. Var.	1.448	1.422	1.400
Unweighted			
PDMP$_{t+2}$	-0.117	-0.108	-0.125*
	(0.091)	(0.090)	(0.071)
Observations	867	867	867
R-squared	0.885	0.882	0.913
Mean of Dep. Var.	8.531	8.156	6.855
Std.Dev. of Dep. Var.	1.448	1.422	1.400
Exclude zero cells			
PDMP$_{t+2}$	-0.088	-0.079	-0.089
	(0.094)	(0.101)	(0.074)
Observations	854	854	854
R-squared	0.923	0.921	0.947
Mean of Dep. Var.	8.531	8.156	6.855
Std.Dev. of Dep. Var.	1.448	1.422	1.400

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.9: Effects of Mandatory PDMPs on Foster Cases

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
Control for border effects			
Mandate_{t+2}	-0.080**	-0.100***	-0.091**
	(0.034)	(0.033)	(0.043)
Border Mandate_{t+2}	0.008	-0.002	0.013
	(0.026)	(0.042)	(0.034)
Observations	371	371	371
R-squared	0.996	0.994	0.994
Mean of Dep. Var.	8.711	8.338	6.890
Std.Dev. of Dep. Var.	0.908	0.967	0.973
Unweighted			
Mandate_{t+2}	-0.106***	-0.111***	-0.129
	(0.039)	(0.039)	(0.100)
Observations	371	371	371
R-squared	0.994	0.993	0.989
Mean of Dep. Var.	8.711	8.338	6.890
Std.Dev. of Dep. Var.	0.908	0.967	0.973
Exclude zero cells			
Mandate_{t+2}	-0.078**	-0.100***	-0.089**
	(0.034)	(0.034)	(0.043)
Observations	371	371	371
R-squared	0.996	0.994	0.994
Mean of Dep. Var.	8.711	8.338	6.890
Std.Dev. of Dep. Var.	0.908	0.967	0.973

Notes - All estimates include time-varying control at the state level for the share of female, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant PF. Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table A.10: Effects of Mandatory PDMPs on Foster Cases (IHS), controlling for CPS staffing

	(1) IHS removals	(2) IHS neglect cases	(3) IHS physical abuses
Mandate $_{t+2}$	-0.035	-0.045	-0.054
Observations	317	317	317
R-squared	0.997	0.995	0.994
Mean of Dep. Var.	4548	3461	768.3
Std.Dev. of Dep. Var.	5349	4806	1033

Notes - All estimates include time-varying control at the state level for the share of female, size of CPS staff, Hispanic, African-American, White, foreign-born, non-citizen population, average family income (log), unemployment rate, children population (0-18), year and state fixed effects, state-specific time trends and the following laws/regulations: Good Samaritan laws, Doctor Shopping, Pain Clinic regulations, Physician exams, require ID, and tamper-resistant prescription form requirement. Data on children who were assigned to foster care because of drug-related abuses are drawn from the National Child Abuse and Neglect Data System (NCANDS) Agency File,(2000-2016). Standard errors adjusted for clustering at the state level are reported in parenthesis. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.