IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 11470

The Effects of Mandatory Prescription Drug Monitoring Programs on Foster Care Admissions

Rania Gihleb
Osea Giuntella
Ning Zhang

APRIL 2018

I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 11470

The Effects of Mandatory Prescription Drug Monitoring Programs on Foster Care Admissions

Rania Gihleb
University of Pittsburgh and IZA

Osea Giuntella
University of Pittsburgh and IZA

Ning Zhang
University of Pittsburgh

APRIL 2018

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

The Effects of Mandatory Prescription Drug Monitoring Programs on Foster Care Admissions*

The opioid epidemic is a national public health emergency. As the number of fa- tal overdoses and drug abuse skyrockets, children of opioid-dependent parents are at increased risk of being neglected, abused or orphaned. While some studies have examined the effects of policies introduced by states to restrict prescription drug supply on drug abuse, there is no study analyzing their effects on children. This paper estimates the effect of must-access prescription drug monitoring programs (PDMPs) on child removals. To identify the effects of the programs on foster care caseloads, we exploit the variation across states in the timing of adoption of must-access 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 caseloads. 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 cases of child neglect. There is also evidence of significant reductions in removal cases associated with child physical abuse.

JEL Classification: I12, I18, J13
Keywords: opioid epidemic

Corresponding author:
Rania Gihleb
Department of Economics
University of Pittsburgh
4901 Wesley W. Posvar Hall
230 South Bouquet Street
Pittsburgh, PA 15260
USA
E-mail: gihleb@pitt.edu

* We are grateful to all the seminar attendees at the University of Pittsburgh. We benefitted from comments from Janet Currie, Mark Borgshulte, Jason Cook, and Betsey Stevenson. We are thankful to the National Data Archive on Child Abuse and Neglect for providing the data on foster care caseloads and child maltreatment.

1 Introduction

The United States are in the midst of an opioid overdose epidemic. Drug mortality rose by 300% between 1999 and 2016. In 2016, the US experienced the largest annual increase in drug overdose deaths ever recorded. 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). Public health officials consider the current opioid epidemic crisis the worst drug crisis in America history.

As recently highlighted by Quast et al. (2018), a critical aspect of this drug crisis are 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 with a 6.7% increase with respect to 2013. This surge is in large part 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 number of drug-related foster care caseloads have increased by 66% (Figure 2). These increases in the foster care population generate significant monetary and non-

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

monetary costs. Previous research estimate that the fiscal costs of a child in foster care is approximately $20,000 (Zill, 2011) and documents that foster care placement can have large detrimental effects on children long-term outcomes (Doyle Jr, 2007, 2008). Of course this is only a part of the costs as child abuse and neglect have long-run effects on human capital, health outcomes and have been shown to increase the likelihood of engaging in crime and of substance abuse (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. Currently, most states have adopted an operational PDMP, but only a few states mandated their use. The main contribution of this study is to evaluate the effects of prescription drug monitoring programs on child removals. To 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) analyzed the effect of meth 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. However, a limitation of their empirical strategy is that it only exploits national variation in meth prices and thus cannot control for unobserved time-varying factors that may have caused changes in foster care caseloads. 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.

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. Consistent with previous studies analyzing the effects of PDMPs on drug abuse (Buchmueller and Carey, 2017; 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%. 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, our results suggest that 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. While the reasons behind the opioid epidemic are multiple have also been linkeds to long-run socio-economic decline (Case and Deaton, 2015), 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 he 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 and can help identifying patients who are receiving multiple prescriptions and may contribute to the epidemic. Some states made the use of the database mandatory for physicians. Non-mandated PDMPs do not legally require health professionals to query them. However, since 2007 a few states have know extended their PDMP with mandatory access provisions which require doctors and pharmacies to query PDMP before prescribing a controlled substance.

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 drug abuse (Simoni-Wastila and Qian, 2012; Meara et al., 2016). On the contrary, recent papers focusing on the effects of PDMP 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, 2017; Patrick et al., 2016; Dave et al., 2017; Borgschulte et al., forth.; Mallatt, 2017).

To the best of our knowledge there is no study analyzing the effects of PDMP programs on foster care caseloads. In our analysis, we distinguish the effects of operational PDMPs from the effects of program that introduced mandatory access.

2.2 Data

Data on foster-care cases are drawn from the Adotpion and Foster Care Analysis and Reporting System (2000-2015). 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 foster care data files contain information on child demographics including gender, birth date, race, and ethnicity.We calculated the number of foster-care cases by year and state.

In addition, we collected county level controls from the Population and Housing Unit Estimates (PHUE, 2000-2015), the US Census (2000) and the American Community Survey (2001-2015). We use data from the PHUE to calculate child population and the share of children who were victims of child maltreatment. We include data on age composition, share of African-american population, share of Hispanic population, median income, gender composition, and unemployment rate drawn from the 2000 US Census and the 2001-2015 American Community Survey. Finally, 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 caseloads to drug monitoring programs we employ an event-study methodology and estimate the following equation:

$$Child_{st} = \delta_s + \phi_t + \sum_{-4}^{4} \gamma_t Mandate_{s,t-\tau} + X_{st} + \pi_s(\delta_s * t) + \epsilon_{st} \qquad (1)$$

where $Child_{st}$ is the number of new foster-care admission in year t in state s. Given the skewed distribution of foster care caseloads 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 PDMP in year t. X_{st} are a set of time-variant state level controls (age composition, share of African-american 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; and $\delta_s * t$ are state specific time trends. Standard errors are clustered at the state level. All estimates are weighted by child population.

Dave et al. (2017) show that adopters of mandatory access provisions were very similar to states having a PDMP but who did not adopt such provisions. For this reason, to investigate the role of Mandatory access PDMPs, we restrict the analysis to states with an operational PDMP. The underlying assumption is that the states that had an operational PDMP 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 differences-in-difference specification. Our identification strategy relies on the assumption that 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. In particular, we identify the effects of the program exploiting 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, 2017; Dave et al., 2017) and based on the dynamic response found in our event study that show the effects of mandatory PDMPs materializes two years after the enactment, we use a two-year lag to estimate our difference-in-difference model. Lagged effects are explained

[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

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.

In practice, we estimate the following OLS model

$$Child_{it} = \alpha + \beta Mandate_{i,t-2} + \psi X_{it} + s_i + \gamma_t + \epsilon_{it} \tag{2}$$

where $Child_{it}$ is the number of abuses or foster-care admission in year (or month) t in state i. $Mandate_{i,t+2}$ is an indicator for whether state i has introduced a must-access Prescription Drug Monitoring Program by year t. X_{it} are a set of time-variant state level controls (age composition, share of African-American 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). In addition, 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

Over the last few years there has been a sharp increase in the number of child removals. 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 3).

Table 1 provides summary statistics of our main outcomes of interest. There were on average approximately 4,500 child removals in a state-year. The two main reason for removals are parental neglect and parental drug abuse. In 70% of the cases, removals were associated with parental neglect, while in 31% of the removals were associated with parental drug abuse. The share of removals associated with parental drug abuse rose from 22% in 2000 to 39% in 2015.

4.2 PDMPs and Foster Care Caseloads

In Figures 4-5, 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 PDMP on child removals (Figure 4). On the contrary, following the adoption of must-access PDMPs we observe a marked decline in the number of child removals (Figure 5. The effect of the Mandates becomes significant two years after the adoption of the mandate. For this reason, our difference-in-difference strategy concentrates on the effects of must-access mandates two years after the implementation of the program.

Table 2 presents the estimated effects of PDMPs on the number of children in foster care by main reason of removal. We find no evidence of significant effects of PDMP on child removals. However, mandatory PDMPs had significant effects on removals reducing both cases associated with neglect and physical abuse (Table 3). The magnitude of the effect is economically significant. The introduction of mandatory procedures reduced child removals by 8%. Foster-care cases associated with neglect and physical abuse reduced by respectively 9% and 10%. These results imply a reduction of 467 removals per year or 0.27 less cases per 1000 children (Table A.2, Panel A and B). Table A.3 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.

We don't find significant effects among Blacks (Table A.4), while the effects are larger among children aged 0-12 (Table A.5).

Our baseline findings suggest that must-access PDMPs may substantially reduce the costs associated with child removals. With a back of the envelope calculation based on previous estimates on the costs of child removals, our results imply that must-access PDMPs reduced costs associated with child removals by approximately 476 million dollars per year, or 4.76 billion in 10 years.

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.

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 caseloads, mandatory PDMP substantially reduced cases of child removals (-10%) with significant reductions in the number of cases associated with neglect and physical abuse. Given the evidence on the long-lasting effects of child maltreatment and foster care, our findings suggest that the human capital, health and economic cost of the opioid crisis may be very large. At the same point, 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 are not negligible. 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.

References

Alpert, A., Powell, D., Pacula, R. L., 2017. Supply-side drug policy in the presence of substitutes: Evidence from the introduction of abuse-deterrent opioids. Tech. rep., National Bureau of Economic Research.

Borgschulte, M., Corredor-Waldron, A., Marshall, G., forth. A path out: Prescription drug abuse and suicide. Journal of Economic Behavior and Organization.

Buchmueller, T. C., Carey, C., 2017. The effect of prescription drug monitoring programs on opioid utilization in medicare. NBER Working Paper.

Case, A., Deaton, A., 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), 15078–15083.

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

Currie, J., Spatz Widom, C., 2010. Long-term consequences of child abuse and neglect on adult economic well-being. Child maltreatment 15 (2), 111–120.

Dart, R. C., Surratt, H. L., Cicero, T. J., Parrino, M. W., Severtson, S. G., Bucher-Bartelson, B., Green, J. L., 2015. Trends in opioid analgesic abuse and mortality in the united states. New England Journal of Medicine 372 (3), 241–248.

Dave, D. M., Grecu, A. M., Saffer, H., 2017. Mandatory access prescription drug monitoring programs and prescription drug abuse. NBER Working Paper.

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

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

Dube, S. R., Felitti, V. J., Dong, M., Chapman, D. P., Giles, W. H., Anda, R. F., 2003. Childhood abuse, neglect, and household dysfunction and the risk of illicit drug use: the adverse childhood experiences study. Pediatrics 111 (3), 564–572.

Kilby, A., 2015. Opioids for the masses: welfare tradeoffs in the regulation of narcotic pain medications. Cambridge: Massachusetts Institute of Technology.

Laxmaiah Manchikanti, M., Standiford Helm, I., MA, J. W. J., PhD, V. P., MSc, J. S. G., DO, P., et al., 2012. Opioid epidemic in the united states. Pain physician 15, 2150–1149.

Mallatt, J., 2017. The effect of prescription drug monitoring programs on opioid prescriptions and heroin crime rates.

Meara, E., Horwitz, J. R., Powell, W., McClelland, L., Zhou, W., O'malley, A. J., Morden, N. E., 2016. State legal restrictions and prescription-opioid use among disabled adults. New England Journal of Medicine 375 (1), 44–53.

Oster, E., 2017. Unobservable selection and coefficient stability: Theory and evidence. Journal of Business & Economic Statistics, 1–18.

Pacula, R. L., Powell, D., Taylor, E. A., 2015. Does Prescription Drug Coverage Increase Opioid Abuse?: Evidence from Medicare. National Bureau of Economic Research.

Patrick, S. W., Fry, C. E., Jones, T. F., Buntin, M. B., 2016. Implementation of prescription drug monitoring programs associated with reductions in opioid-related death rates. Health Affairs 35 (7), 1324–1332.

Paulozzi, L. J., Mack, K. A., Hockenberry, J. M., 2014. Vital signs: variation among states in prescribing of opioid pain relievers and benzodiazepines-united states, 2012. Morbidity and Mortality Weekly Report 63 (26), 563–568.

Quast, T., Storch, E. A., Yampolskaya, S., 2018. Opioid prescription rates and child removals: Evidence from florida. Health Affairs 37 (1), 134–139.

Rudd, R. A., 2016. Increases in drug and opioid-involved overdose deathsunited states, 2010–2015. MMWR. Morbidity and mortality weekly report 65.

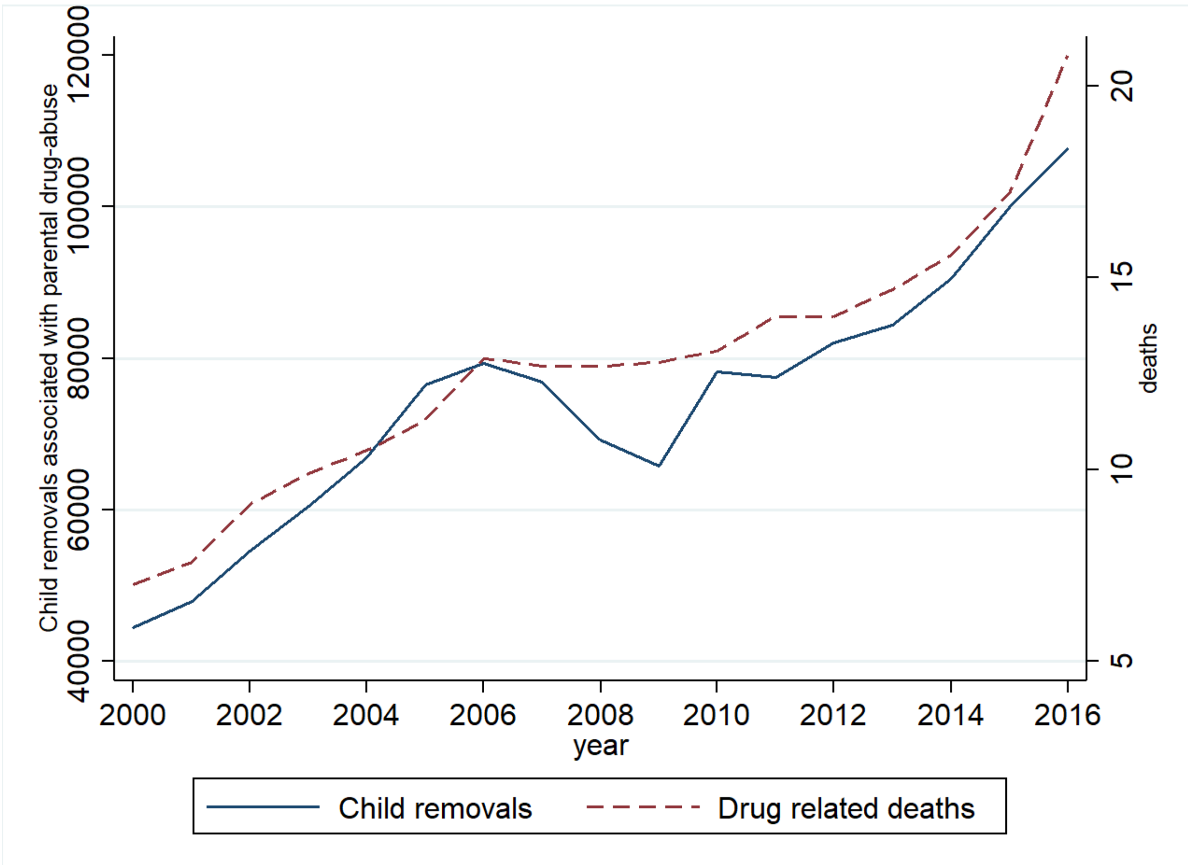
Ruhm, C. J., 2018. Deaths of despair or drug problems? Tech. rep., National Bureau of Economic Research.

Simoni-Wastila, L., Qian, J., 2012. Influence of prescription monitoring programs on analgesic utilization by an insured retiree population. Pharmacoepidemiology and drug safety 21 (12), 1261–1268.

Zill, N., 2011. Better prospects, lower cost: The case for increasing foster care adoption. Adoption Advocate 35, 1–7.

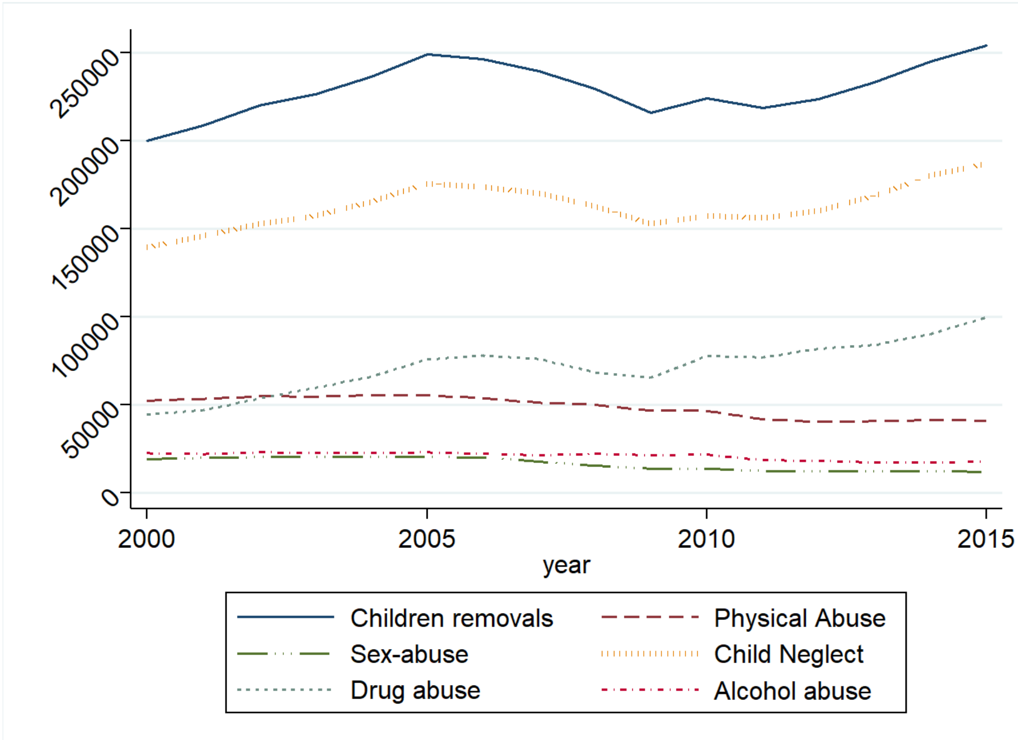
Figures and Tables

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



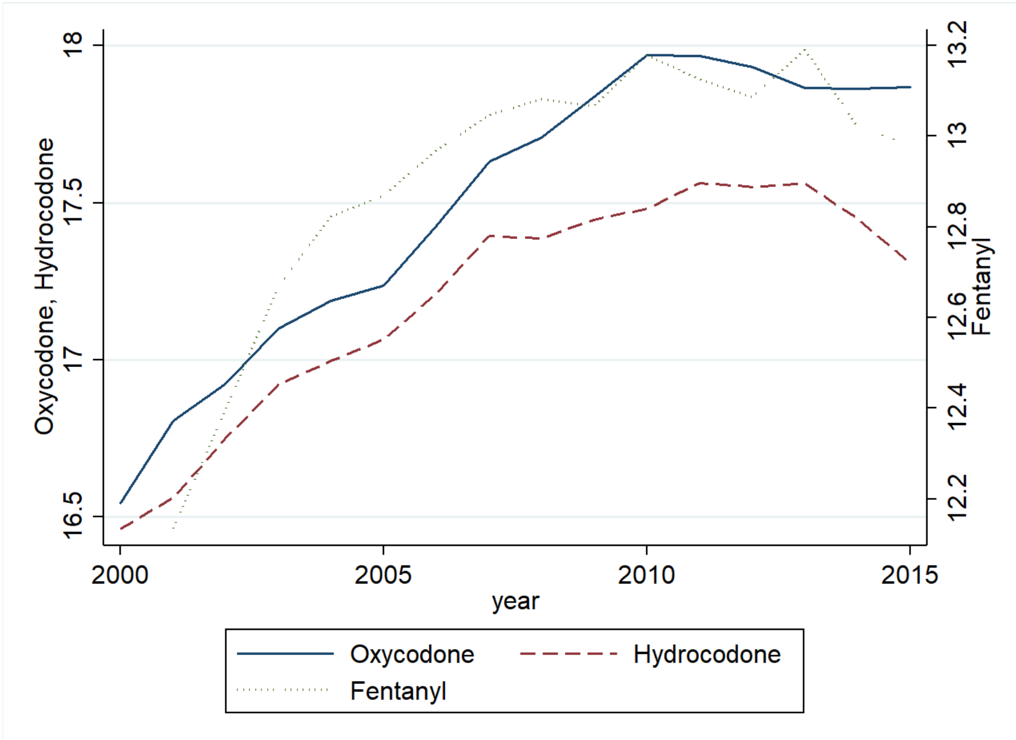
Notes - Data on drug-related deaths are drawn from CDC database on detailed mortality causes. The Underlying Cause of Death database contains mortality and population counts for all U.S. counties. Data are based on death certificates for U.S. residents. Each death certificate identifies a single underlying 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 (2000-2016).

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



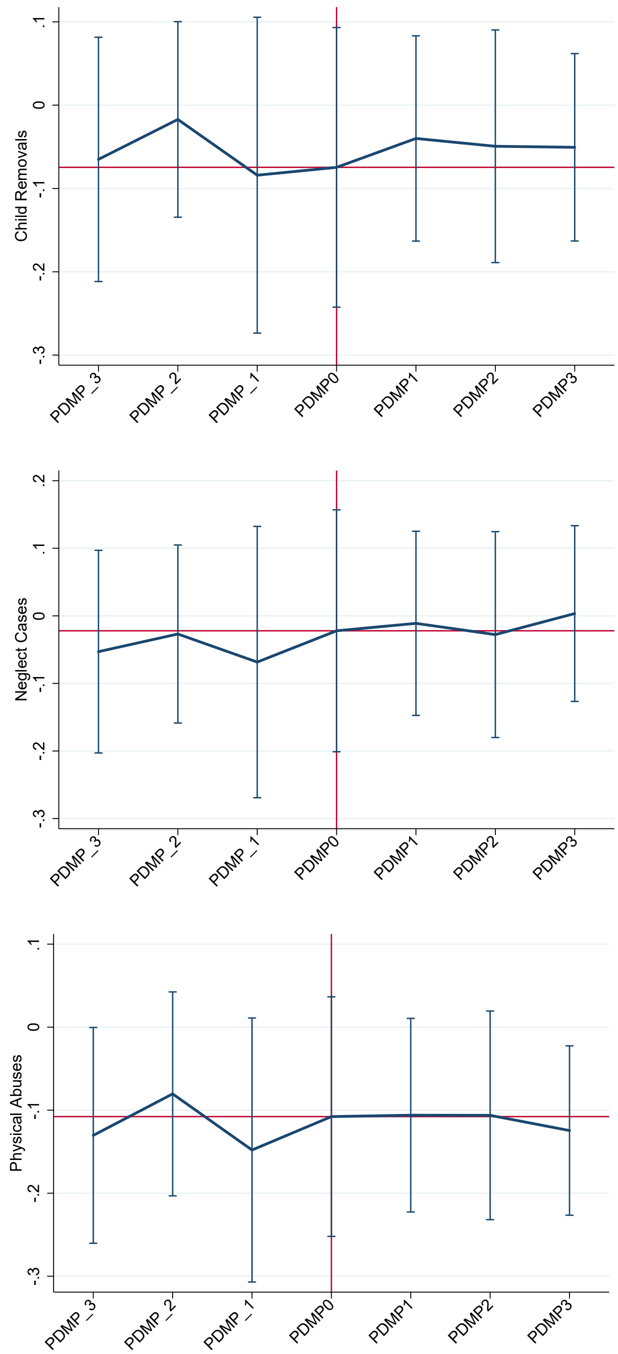
Notes - Data are drawn from the Automated Reports and Consolidated Ordering System (ARCOS) provided by the U.S. Department of Justice Drug Enforcement Administration, Diversion Control Division. Data cover the period 1999-2015.

Table 1: Summary Statistics, AFCARS (2000-2015)

	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

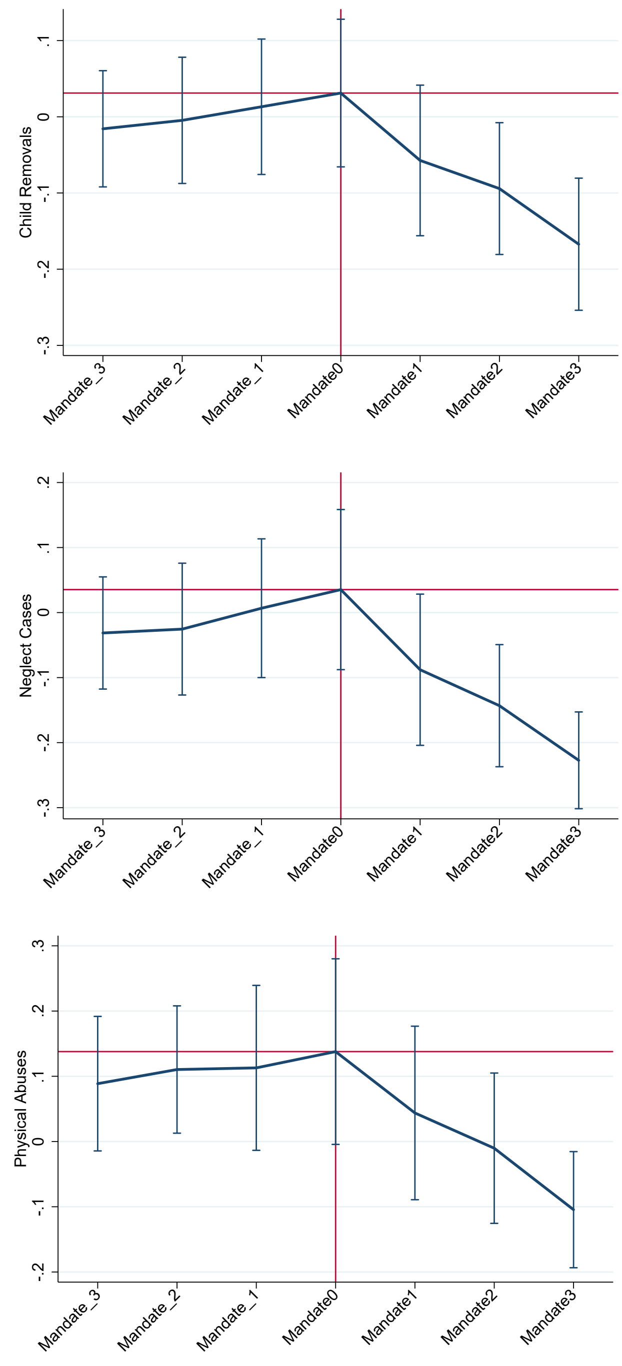
Notes - Data on children who were assigned to foster care because of drug-related abuses are drawn from the Adoption and Foster Care Analysis and Reporting System (AFCARS), Foster Care File (2000-2015). The table reports unweighted summary statistics by state and year for the main outcome variables in all US states. Data spans years 2000 to 2016.

Figure 4: PDMP Event Study-Child Removal



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).

Figure 5: Mandate Event Study-Child Removal



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).

Table 2: Effects of PDMP on Foster Cases (IHS)

	(1) IHS abuse cases	(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).

Table 3: Effects of Mandatory PDMP on Foster Cases (IHS)

	(1) IHS abuse cases	(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).

Appendix

Table A.1: Effects of PDMP on Foster Cases

	(1) abuse cases	(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).

Table A.2: Effects of Mandatory PDMP on Foster Cases

	(1) abuse cases	(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).

Table A.3: Must-access PDMP 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 withPhysical 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

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

	(1) IHS abuse cases	(2) IHS neglect cases	(3) IHS physical abuses
Whites			
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
Blacks			
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).

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

	(1) IHS abuse cases	(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).