Understanding the Effect of the Opioid Epidemic on Child Maltreatment

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Introduction

This appendix is an overview of the CSSAT project, conducted as part of the CMI Data Linkages work. The site team authored the appendix, and the Mathematica team worked with the site to ensure consistency in information, level of detail, and presentation across sites.

Overview

The public has raised concerns that the current opioid epidemic is increasing the risk of child maltreatment and contributing to higher caseloads in child welfare systems (Brundage and Levine 2019). This project expanded knowledge about the validity of these concerns. Based on several sources of data on a state population, the CSSAT project used multiple indicators of child maltreatment and involvement with the child welfare system. Individual and community-level risk factors were included in the analysis, which can guide the use of prevention and intervention services.

Partnership history

Overall, the state of Washington has been supportive of linking data from different entities and sharing the linked data with research partners. The state-administered child welfare agency has had a data sharing agreement with the University of Washington (UW) School of Social Work since July 1, 2007.

The partnership includes research staff (researchers and data linkers) and data partners (state agency staff). The research staff included three people: Joseph A. Mienko, principal investigator; Rebecca Rebbe, co-principal investigator, and Karen Segar. Dr. Mienko oversaw all aspects of the project and is the main contact with the state partners. Dr. Rebbe was the primary data analyst, even after she moved to the University of Southern California. Ms. Segar, the data manager at the University of Washington Harborview Injury and Prevention Research Center, completed the data linkages, which the institutional review board (IRB) requires someone outside the research analytic team to conduct.

The data partners were Tammy Cordova of the Department of Children, Youth & Families (DCYF) Office of Innovation, Alignment, and Accountability (OIAA), where she serves as the data and reporting administrator; Sarah Veele of OIAA, who is the research and analysis administrator; Katie Hutchinson of the Washington Department of Health, where she serves as the data manager and epidemiology supervisor (she facilitated access to vital records and hospital admission records); and Mariana Rosenthal, manager and epidemiologist at the Washington Department of Health Prescription Management System, who facilitated access to data from the prescription management system.

The project expanded on work using linked administrative data in the context of a preexisting ongoing relationship. Although there is an ongoing agreement for DCYF to share child protective services (CPS) data with the UW School of Social Work, the study needed new approvals from the Department of Health (DOH) and the IRB to get updated data (births, hospitalizations, and deaths). According to state law, the Washington State IRB had to approve the work because this project used Washington State administrative data concerning clients of a state agency.

The cornerstone of this partnership is an annual work plan and an associated data sharing agreement with OIAA. The data sharing agreement facilitated the quarterly transfer of more than 100 tables from the data warehouse for Washington's transitional Comprehensive Child Welfare Information System (CCWIS), which is known as FamLink.

The relationship with DCYF facilitated access to DCYF data. Given the topical focus of the project, DCYF was the main point of contact for disseminating findings related to this project and the parent study, the Risk of Death and Injury Study, as a whole (see Rebbe et al. 2019, 2020). The study team's relationships with DOH only involved the acquisition of data needed for this study.

Background

The purpose of this study was to examine the association between county-level rates of opioid overdose events and child maltreatment indicators. Specifically, the study examined associations between county-level rates of opioid overdose events in Washington State, as measured by hospitalizations and deaths, with rates of CPS (1) reports, (2) substantiations, (3) removals, and (4) maltreatment-related hospitalizations. The study built on and extended previous research in two ways. First, it focused on opioid overdose events specifically. By disaggregating opioids from general parental substance (ab)use, the opioid epidemic's specific impact on the child welfare system can be clarified. Second, it used repeated and nuanced measures of opioid overdoses events, CPS involvement, and child maltreatment over an extended period of time to capture a more precise and accurate picture of temporal associations (Rebbe et al. 2020).

Research Questions

1. How does individual-level and county-level opioid use/misuse impact the risk of maltreatment for children and families in Washington State?
    - To what extent do counties exhibiting pronounced indications of an opioid public health emergency, as indicated by opioid overdose hospitalizations and deaths, also exhibit increased rates of child maltreatment?
    - To what extent do individual-level maternal opioid prescriptions affect in utero opioid exposure diagnoses?

2. How does opioid use/misuse impact contact with the child welfare system for children and families in Washington State?
    - Is there disproportionate testing of children/mothers for prenatal substance exposure in certain populations (racial/ethnic groups, people with different insurance status, maternal age) compared to appropriate referent groups in the entire population of children born in the state during the study time period?
    - If disproportionate testing exists, does the disproportionate representation result in disproportionate reporting rates for families experiencing opioid use/misuse or prenatal opioid exposure?

3. How do indications of opioid use/misuse or prenatal opioid exposure (POE) at the family and county level impact substantiation and placement decisions within households under investigation for maltreatment?

The project could not access the data required to answer Research Question 2. Although DOH saw value in the question, the data's sensitive nature was a persistent barrier. DOH did not have the resources available to link the data on its own, and was not able to share personally identifiable information (PII) with the team members so they could make the linkages.

Data

Sources

The state of Washington provided the data for the study—specifically, CPS records, birth records, hospital admissions, and death records.

- Birth records (approximately 1.5M rows): Records of all live births in Washington State from 1999 through 2017, a 19-year birth cohort maintained by DOH.
- Hospital admissions records (approximately 13M rows): Records from the Comprehensive Hospital Abstract Reporting System (CHARS) from 1999 through 2017, a DOH system collecting patient-level information on inpatient and community hospitals for all nonmilitary hospitals in Washington State.
- Death records (approximately 1.1M rows): Mortality records for all fatalities in Washington State from 1999 through 2017, maintained by DOH.
- CPS records
    - Person records (approximately 3.2M rows): Records for all persons with data in FamLink
    - Intake records (approximately 2M rows): Records from the Washington State child welfare system for all reports of child maltreatment from 1999 through 2018
    - Screening records (approximately 1M rows): Records from the Washington State child welfare system for all reports of child maltreatment that resulted in an investigation or assessment from 1999 through 2018
    - Removal records (approximately 100K rows): Records from the Washington State child welfare system for all removal episodes from 1999 through 2018

Linking process

The project used a combined (probabilistic and deterministic) approach to link records. The goal was to match family members across data sources, so birth and CPS records were used to identify parents of children.

The linkage process made use of the following data elements in all of the aforementioned data:

- Full names for children listed in the birth cohort, and the parents of the children
- Dates of birth for children listed in the birth cohort, and the parents of the children
- Records of race, ethnicity, and tribal membership at birth for children listed in the birth cohort and the parents of the children
- The geographic residence of the child or the child's parents at the time of a given event in the data
- The full or partial Social Security number for a child or the child's parents

The project used a combination of deterministic (blocking) and probabilistic linkages as outlined by Enamorado et al. (2019). Project staff decided to use a relatively new product from Amazon Web Services (AWS) which better accommodated the unique arrangement they had with the state with respect to linkage personnel (that is, a single person has direct access to PII).

Specifically, the project team used AWS Glue, a component of the HIPAA-compliant AWS Lake Formation tools now offered by AWS.[19] The key feature of the AWS Glue for his ongoing linkage work was FindMatches, a machine learning transformation algorithm that is a tool to identify and remove duplicate records across data sets in a manner that requires little action on the part of the linking staff. In this case, the same algorithm is used to identify and link duplicate records across data sets. The AWS Glue Developer Guide outlines the entire process.[20]

The one limitation of the approach is that FindMatches is truly a black-box algorithm. It was clear from reviews of the system logs that FindMatches used Apache Spark and a variation on k-means clustering.[21] Accuracy can be tested through more traditional post hoc approaches (for example, examination of the proportion of infant CPS referrals present in state birth records). Amazon also provides accuracy and precision metrics typical of all machine learning models. Overall, the team believed the benefits of the ease of use and good fit for the small team outweighed the opaqueness of the underlying algorithm.

Given the black-box nature of the algorithm, the AWS Glue interface limited the tuning criteria to those available – namely, balancing the risk of false positives (vs false negatives) in terms of recall versus precision, and cost versus accuracy. The chosen approach was to follow the logic of Zech et al. (2016) and err on the side of avoiding false-positive matches. The project staff maximized for accuracy (that is, conformity with true positives) and precision (that is, repeatability); and thus trained its algorithm with accuracy (versus cost) and precision (versus recall) parameters set to 0.9.[22]

Washington has a highly mobile population. Project staff were concerned that linking individuals across data sets would result in insufficient power to conduct the planned analyses. The AWS Lake Formation tool addressed this concern by giving the ability to block based on gender, given its use in deterministic linking due to the number of years of data. Additionally, some portion of the unmatched cases may represent migration to a locality outside of Washington. The project staff compared they unmatched case rates to those reported by other CMI Data Linkages sites, which were similar. They also examined U.S. Census migration rates within the same localities to determine if the rate of unmatched cases was unreasonable.

Analytic Methods

The team conducted all analyses in R, after using AWS to link the data.

Research Question 1:

1. How does individual-level and county-level opioid use/misuse impact the risk of maltreatment for children and families in Washington State?

[19] See “AWS Lake Formation” at https://aws.amazon.com/lake-formation/?whats-new-cards.sort-by=item.additionalFields.postDateTime&whats-new-cards.sort-order=desc.
[20] See “Tuning Machine Learning Transforms in Amazon Glue” at https://docs.aws.amazon.com/glue/latest/dg/add-job-machine-learning-transform-tuning.html.
[21] See “K-Means Clustering with Apache Spark” at https://www.bmc.com/blogs/k-means-clustering-apache-spark/.
[22] See Zech et al. (2016) for a fuller explanation of the approach.

The project staff used Bayesian Model Averaging (BMA) to find the variables that were the best fit for each model with the four outcome measures (CPS report rates (regardless of screening decision), CPS substantiation rates, CPS removal rates, and maltreatment-related hospitalization rate). This method considered multiple models simultaneously and used the Bayesian Information Criterion (BIC) to identify the optimal model. After identifying the variables to include in each model, the team ran an ordinary least squares model, followed by a fixed effects panel data model with year and county as the fixed effects. Project staff tested to see if the panel data model was a better fit than the ordinary least squares model, then ran a random effects panel data model and used a Hausman test to identify if the random or fixed effects model was a better fit. For both tests, p-values < 0.05 indicated that the fixed effects model was better than the ordinary least squares or random effects models for the respective tests.

Research Question 3:

3. How do indications of opioid use/misuse or prenatal opioid exposure (POE) at the family and county level impact substantiation and placement decisions within households under investigation for maltreatment?

The project identified children diagnosed at birth with opioid exposure through either the maternal or child ICD-9 diagnostic codes. Project staff ran a multistate survival model identifying three placement outcomes: (1) birth home, (2) out-of-home placement, and (3) hospitalization or death. They included a county rate of opioid-related hospitalization or death, concentrated disadvantage, presence of a CPS report, child sex, birth payment, maternal race, maternal age at birth, and parity as covariates. They completed chi-square analysis on a descriptive distribution table.

Findings

Research Question 1:

1. How does individual-level and county-level opioid use/misuse impact the risk of maltreatment for children and families in Washington State?

Although numerous news reports have stated there is a relationship between the opioid epidemic and child maltreatment, the project found that controlling for other factors in Washington State resulted in no relationship between opioid overdose events and child maltreatment indicators. Initially, the analysis revealed positive, statistically significant relationships between opioid overdose event rates and CPS report rates (regardless of screening decision), CPS removal rates, and maltreatment-related hospitalizations. However, in full panel data models that took a number of factors into consideration, there were no statistically significant relationships identified (Table D.1). Instead, CPS reports and maltreatment-related hospitalizations increased over time, whereas CPS substantiations and CPS removals decreased in the study time period.

The findings may relate to maltreatment policies in Washington State, and should be interpreted within the context of broader systems-level policies and related practices. Although the definition of neglect in Washington State gives weight to parental substance abuse as a factor in child maltreatment, the state does not consider substance abuse maltreatment in and of itself. This ambiguity may lead to fewer reports to CPS than there are in states with more stringent definitions of neglect. Another possible explanation is the lack of resources available in Washington State during the study time period. Following the Great Recession in 2008, Washington State had to make a number of budget cutbacks to address the reduction in state revenue. This included cuts to CPS staff and social worker positions. According to the state’s historical spending trends, salaries and wages for children and family services were more than $32 million lower in the 2011–2013 biennium than in the 2007–2009 biennium (Washington State Fiscal Information 2020). The decrease in substantiations and removals by year found in this study may also reflect CPS workers raising the threshold that warrants substantiation and removal in response to a lack of services available to families (Barnett et al. 1993, Giovannoni 1991).

Table D.1. Panel data model results examining relationship between opioid overdose events and child maltreatment-related outcomes

	Child maltreatment-related outcomes											
	Reports			Substantiations			Removals			Maltreatment-related hospitalizations		
Coefficient	Est.	S.E.	*p*	Est.	S.E.	*p*	Est.	S.E.	*p*	Est.	S.E.	*p*
Opioid overdose event rate	-7.79	4.19		0.07	0.91		-0.04	0.79		0.04	0.09	
Public assistance	0.27	1.25		-0.11	0.63		-0.62	0.32		-0.06	0.03	*
Population younger than 18	-9.52	5.15		-2.39	2.46		1.23	1.20		-0.15	0.14	
Unemployment	1.25	2.16		0.14	0.75		-0.75	0.49		0.04	0.04	
Year 2006	25.45	1.85	***	-1.57	0.65	*	0.001	0.22		0.01	0.02	
Year 2007	27.63	1.84	***	-2.24	1.04	*	-0.25	0.34		0.09	0.05	*
Year 2008	24.98	1.90	***	-2.68	0.84	**	-1.21	0.36	***	0.07	0.03	*
Year 2009	22.91	1.95	***	-3.65	0.87	***	-1.39	0.39	***	0.15	0.04	***
Year 2010	24.43	2.01	***	-3.22	0.92	***	-1.60	0.34	***	0.11	0.03	***
Year 2011	20.35	1.54	***	-3.61	1.10	**	-2.18	0.41	***	0.22	0.03	***
Year 2012	24.91	1.80	***	-3.90	1.07	***	-2.22	0.38	***	0.14	0.04	**
Year 2013	29.31	2.11	***	-2.26	0.96	*	-1.78	0.48	***	0.15	0.03	***
Year 2014	29.24	2.01	***	-3.03	1.07	**	-1.81	0.51	***	--	--	
Year 2015	30.89	2.14	***	-4.08	1.00	***	-2.03	0.43	***	--	--	
Year 2016	32.41	2.24	***	-5.44	1.24	***	-1.78	0.45	***	--	--	
Year 2017	36.97	2.38	***	-4.86	1.09	***	-1.49	0.38	***	--	--	
R^2	0.55			0.19			0.24			0.18		
BIC	3267.518			2367.033			1733.149			-178.7682		

Source: Author analysis.

Note: Rates are per 1,000 in the population. Public assistance, population under 18, and unemployment are *z*-scores. Each model is a fixed effects model. Data on hospitalization rates for child maltreatment were not available after 2013. Est. = estimate. S.E. = standard error. *p* = *p*-value. BIC = Bayesian Information Criterion.

* Significantly different from zero at the .05 level, two-tailed test.

** Significantly different from zero at the .01 level, two-tailed test.

*** Significantly different from zero at the .001 level, two-tailed test.

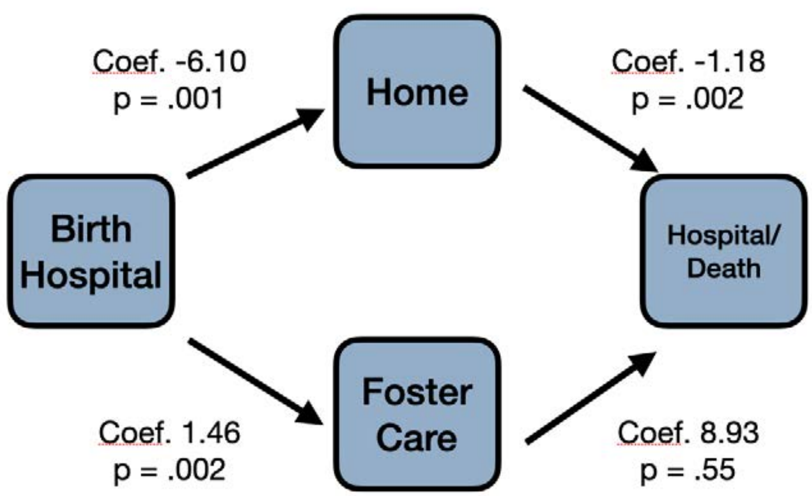
Research Question 3:

3. How do indications of opioid use/misuse or prenatal opioid exposure (POE) at the family and county level impact substantiation and placement decisions within households under investigation for maltreatment?

This analysis examined specific transitions for infants diagnosed with prenatal opioid exposure. The transitions were from (1) birth hospitalization to birth home, (2) birth hospitalization to foster home, (3) birth home (after birth hospitalization) to either a hospitalization or death, and (4) foster home (after birth hospitalization) to either a hospitalization or death. The analysis revealed that as the rates of county opioid overdose events increased (as measured by hospitalizations and deaths), children were less likely to go to their birth home from their birth hospitalization ($p < .001$). In other words, opioid-exposed infants born in counties with high rates of opioid overdose are less likely to go home after birth. Similarly, opioid-exposed infants were more likely to go to out-of-home care (foster care) in counties with higher rates of opioid overdose events ($p = .02$). For opioid-exposed children who do go home after birth, there appears to be a protective effect against experiencing hospitalization or death as the rate of opioid overdose events in the counties they are born in increases ($p = .002$). This remains true even when controlling for whether the child had a subsequent referral to the child welfare system after going home. The opioid overdose rate of birth counties was not associated with the transition from out-of-home placement to hospitalization or death.

A county's rate of opioid overdose events impacts the transitions from birth hospitalization to birth homes, birth hospitalization to foster care, and from birth homes to a hospitalization or death for children diagnosed with prenatal opioid exposure in Washington State. However, it does not impact transitions uniformly. Instead, it appears that the system engages in triaging activities and reserves placements in care for the most severe cases.

Figure D.1. County opioid overdose rate associations with child welfare outcomes



Note: Coef. = coefficient. *p* = *p*-value for coefficient. Home = Return to home. Foster Care = placed in a foster home.

Next steps

The project intends to update the analysis for Research Question 3 using the fully data through 2017. There are additional analyses that will be pursued using the data linked through 2017.

Lessons Learned About Administrative Data Linkage Practices Related to Examining the Incidence and Risk of Child Maltreatment

The 14-year relationship between Partners for Our Children and the State greatly enhanced the project staff's ability to conduct this study. The time and attention needed to sustain the relationship are vital to the ability to address new research questions as they emerge.

The major lesson the team learned during this engagement is the need for a linkage solution that meets the unique needs of a small team with limited access to fully identified data. Within the last month of this project, they were able to identify a new solution,, AWS Glue, that perfectly met the need. Glue is an extract, transform, and load (ETL) service that allows a single person to train a machine learning model on a small extract of records from two or more data sets requiring linkages. On the basis of this training data, Glue programmatically generates Python code that a researcher can run to replicate the patterns observed in the training data to the data as a whole. The only point in the linkage process at which individuals observe PII is during the training procedure, 30- to 60-minute process that the designated data linker for the IRB can manage. This approach to linking data works well for this small team and has allowed them to unblock their linkage process after months of delay.

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