Hospital Variation in Child Protection Reports of Substance Exposed Infants

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Objective To examine whether hospital-level factors contribute to discrepancies in reporting to Child Protective Services (CPS) of infants diagnosed with prenatal substance exposure.

Study design We used a linked dataset of birth, hospital, and CPS records using diagnostic codes (*International Classification of Diseases, Ninth Revision*) to identify infants diagnosed with prenatal substance exposure. Using multilevel models, we examined hospital-level and individual birth-level factors in relation to a report to CPS among those infants prenatally exposed to substances.

Results Of the 760 863 infants born in Washington State between 2006 and 2013, 12 308 (1.6%) were diagnosed with prenatal substance exposure. Infants born at hospitals that served larger populations of patients with Medicaid (OR, 1.25; 95% CI, 1.07-1.45) and hospitals with higher occupancy rates (OR, 1.43; 95% CI, 1.15-1.77) were more likely to be reported to CPS. Infants exposed to amphetamines (OR, 2.58; 95% CI, 2.31-2.90) and cocaine (OR, 2.33; 95% CI-1.92, 2.83) were more likely to be reported and infants exposed to cannabis (OR, 0.62; 95% CI-0.55, 0.70) were less likely to be reported to CPS than infants exposed to opioids. Infants with Native American mothers were more likely to be reported to CPS than infants with white mothers (OR, 1.47; 95% CI, 1.27-1.70).

Conclusions Hospital-level and individual birth-level factors impact the likelihood of infants prenatally exposed to substances being reported to CPS, providing additional knowledge about which infants are reported to CPS. Targeted education and improved policies are necessary to ensure more standardized approaches to CPS reporting of prenatal substance exposure. *(J Pediatr 2019;208:141-7)*.

It is estimated that 298 000 women in the US used illicit drugs or alcohol during pregnancy in 2015, of whom 109 000 used illicit drugs and 105 000 engaged in binge alcohol use.[1] Exposure to drugs in utero has the potential for serious health and developmental harms both in utero and after birth. Serious teratogenic effects are possible when exposure to drugs occurs during the embryonic stage.[2] Effects of exposure during the fetal period include alterations to neurotransmitters and brain organization.[2] Low birth weight has been linked to exposure to cannabis,[3] cocaine,[4] alcohol,[5] amphetamines,[6] and specifically methamphetamine.[7] Amphetamines have also been found to be associated with preterm births,[6] and cannabis exposure increases risk of admission to the neonatal intensive care unit.[3]

After birth, prenatal opioid exposure is associated with neurodevelopmental impairments at 6 months of age[8] and through early childhood.[9,10] Prenatal methamphetamine exposure has been found to impair fine motor skills at 1 year of age.[11] Infants have been identified to be more reactive to stress when prenatally exposed to cocaine.[12] Prenatal alcohol exposure has been linked with issues with mental development at one year,[13] externalizing behavior problems,[14] and academic difficulties.[15]

Federal policies have been established in reaction to concerns regarding prenatally substance-exposed infants. The federal Keeping Children and Families Safe Act of 2003 reauthorized and updated the Child Abuse Prevention and Treatment Act, which included 2 requirements regarding prenatal substance exposure. One required all health personnel to inform the child welfare system of infants who are prenatally exposed to substances (Keeping Children and Families Safe Act, 2003, section 106(b)(2)(A)(ii)). The second mandated that all states have policies and procedures to respond to infants prenatally exposed to drugs. The legislation, which does not mandate testing or screening, was meant to provide early intervention to families, not to act as a punishment.[16]

Despite mandates to report suspected abuse and neglect in every state, research has demonstrated that physicians do not always do so.[17,18] Reasons for not reporting include a lack of understanding of mandated reporting laws,[19] previous poor experiences with CPS,[19-21] previous experience testifying or being deposed

BIC	Bayesian information criterion
BMA	Bayesian model averaging
CPS	Child Protective Services
ICD-9	*International Classification of Diseases*, *Ninth Revision*
NOS	Not otherwise specified

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in a maltreatment case,[19] concerns about damaging the relationship with the child's family,[19] and concerns about outcomes after reporting to CPS.[22]

A recent study examined reports to CPS within a population-based birth cohort of infants in California using a linked dataset from birth, hospital, and Child Protective Services (CPS) records.[23] This study found that infants diagnosed as substance-exposed through the *International Classification of Diseases, Ninth Revision* (ICD-9) codes on their hospital records comprised 40.6% of all reports to CPS in the neonatal period (28 days). However, only 53.4% of infants diagnosed with prenatal substance exposure were reported to CPS within the neonatal period. The reporting proportion varied by substance from a low of 36.1% with an alcohol exposure diagnosis to a high of 72.1% of those diagnosed with cocaine exposure. Further, the authors found no evidence that substance-exposed black or Hispanic infants were more likely to be reported to CPS than white substance-exposed infants. This study did not include data on hospital-level variability.[23]

Similar to California, Washington state has no explicit requirement for reporting substance exposed infants to CPS. However, the definition of neglect or abuse is broad enough that substance exposed infants could be considered to be included and it specifically states that the role of a parent's substance abuse should be "given great weight" (Revised Code of Washington 26.44.020 (16)). Further, the Washington State Department of Health has published guidelines on how hospitals should respond to substance exposed infants including that all positive toxicology tests (maternal or child) should be reported to CPS.

We conducted a statewide retrospective cohort study to examine hospital-level and birth-level differences in reporting substance-exposed infants to CPS. Enhancing our understanding of these potential differences will provide insights on CPS reporting discrepancies and whether improved policies are necessary at the hospital level.

Methods

We prepared an analytic dataset consisting of the birth records linked to CPS records for all children born in Washington State from 2006 through 2013, the most recent years available. The infant's birth records were examined for ICD-9 diagnosis codes related to substance exposure and/or substance abuse. Newborns were included in the study if they or their mother had an ICD-9 code related to substance exposure (ICD-9 codes are presented in **Appendix 1** [available at www.jpeds.com]). A total of 12 308 children were included in the study, representing 1.62% of the 760 863 children born in Washington State during that time period. We excluded infants with gestational ages of less than 22 weeks (n = 29), the current cutoff for viability. This study was part of a larger investigation regarding child welfare involvement and child injury/health risks approved by the Washington State Institutional Review Board.

The dependent variable was whether or not (ie, dichotomous) a hospital reported a child to CPS within the early neonatal period (within 7 days of birth). To capture this response, contacts with the child welfare system were restricted in this study to those contacts initiated by reports from physical or mental health professionals (including social workers employed by the child welfare agency because the reports may have been made directly to CPS workers as opposed to the reporting hotline).

Individual Birth-Level Exposures

Thirteen measures from the infant's birth record were included. Maternal race was coded into 3 dummy variables for each of the race/ethnicity categories with at least 500 exposure births: black, Hispanic, Native American, with our referent category as white (because it was the largest). Consistent with state child welfare trends, Asians were underrepresented in our study population and did not reach our 500 exposure threshold. A binary variable indicating late or no prenatal care was coded as a 1 if the mother started prenatal care in the third trimester or not at all. The payment for the birth was coded as binary reflecting whether or not public funds were used. A binary variable of low birth weight was coded if an infant weighed less than 2500 g at birth. The mother's age at birth and the infant's gestational age were also included. A dichotomous variable was constructed to indicate whether the infant was the mother's first birth or not. The continuous measures were standardized by subtracting their means and dividing by 2 SD, as suggested by Gelman, allowing for direct comparisons with untransformed binary measures.[24]

The most frequent infant substance exposures (with at least 500 exposure births) were included with each category constructed as binary (cannabis, amphetamines, cocaine, and alcohol) with the largest, opioids, serving as the referent category. Exposure to tobacco was not included because of the small likelihood tobacco exposure would warrant a CPS report. Some subjects (37%) were categorized as dependence or exposure not otherwise specified (NOS). Because the type of substance is of clinical importance, we inferred the type of substance exposure for these subjects using an iterative imputation method that has been demonstrated to perform well empirically.[25] More details regarding our methods for this imputation are located in **Appendix 2** (available at www.jpeds.com).

Hospital-Level Exposures

Publicly available data about the hospitals in which the infants were born were compiled from the Washington State Department of Health website. Variables for each hospital included the number of births in a year, the overall average length of stay for patients, the occupancy percentage of the hospital's beds, and percent of the hospital's revenue that came from Medicaid payments for the time period of the study (2006-2013). Each of the variables was then averaged over the time period. Hospital county-level information for the county the hospital is located in included the county's binary rural status according to Washington State Statute that defines a county as being rural if it has a population density less than 100 persons per square mile, or if the county is smaller than 225 square miles (RCW 82.14.370). Because research has demonstrated that community-level risk factors can impact individual substance abuse,[26] we also examined publicly available variables from the Washington State Department of Social and Health Services Research and Data Analysis Division's Risk and Protection Profile for Substance Abuse Prevention report. These included the 5-year standardized indicator rates per 1000 adults of alcohol or drug-related deaths, adult clients of state-funded alcohol or drug services, and adult drug law violation arrests for the county.

Statistical Analyses

When there are many candidate independent variables and a lack of theory to act as guidance, there are a few methods for statistical model selection. Commonly, stepwise approaches are used, adding and deleting variables sequentially and relying on changes in the explained variance to determine the optimal model.[27] However, this method is subject to concerns such as only being able to consider one model at a time and underestimates of model uncertainty.[28] A different method that has been growing in its application, Bayesian model averaging (BMA), directly addresses these concerns in its approach by considering multiple models simultaneously and comparing non-nested models.[29-31] Specifically, BMA uses the Bayesian information criterion (BIC) approximation to the posterior model probabilities, completing an "exhaustive search and finds the globally optimal model."[30] Indeed, BMA has been found to perform better than stepwise approaches in medical studies[28,32,33] Thus, we used BMA, via the eponymous R package[34] to identify which variables to include in our final model.

Using the variables identified in the best model from BMA, we then ran multilevel and conventional logistic regression models to test for birth-level and hospital-level differences. The hospital-level variables were modeled as fixed effects. We used the function, glmer, from the R package lme4[35] for the multilevel model and the glm function from the stats package[36] for the logistic regression model. We compared the BICs to identify which model best fit the data.

Results

Descriptive Results

Descriptive results are presented in Table I for all of the study variables at both the individual birth level and at the hospital level before standardization. The majority of substance-exposed infants were white (70.0%), which is higher than 60.3% of the general population births during this time period. The proportion of substance-exposed infants born to Native American mothers (10.4%) was about 5 times the proportion of the general population during this time period (2.1%), and for infants born to black mothers the proportion was just under twice the rate in the general population (8.5% compared with 4.7% in the general population). The proportion of prenatal substance exposed infants was smaller for Hispanic infants (7.9%) compared with the general population (15.6%). Opioids were the most common substance exposure (48.0%). Just more than one-half of the hospitals were considered rural (51.6%; Table I).

Modeling Results

The 4 best models based on BMA, as indicated by the highest posterior probabilities, which represent "the likelihood that the candidate model is the 'correct' model that produced the data,"[37] are presented in Table II. There was very strong evidence for the inclusion of 12 variables as indicated by the inclusion probabilities of 100% based on the Raftery[29] guidelines: hospital Medicaid revenue percentage, hospital number of births, hospital average length of stay, hospital occupancy percentage, county drug arrests, infant amphetamine exposure, infant cannabis exposure, infant cocaine exposure, maternal race/ethnicity (as indicated by maternal Native American race), maternal late or no prenatal care, public insurance birth pay, and low birth weight. Two additional variables, rural hospital county (73.3) and maternal age (56.8), were categorized as weak with regard to their evidence for inclusion, but were included as this evidence stills supports their inclusion.

Table I. Descriptive statistics of exposure variables

Variables	Mean/Percent	SD	Range
Hospital-level exposures			
No. of births at hospital in a year*	1225.7	1409.1	8-7333
Overall average length of patient stay*	3.5	0.9	2.0-6.3
Occupancy percentage*	47.9	19.3	11.0-80.9
Percent of hospital revenue from Medicaid*	16.2	7.7	0.1-41.9
Hospital rural status	51.6		0-1
5-year rate of alcohol/drug-related deaths†	12.5	0.8	10.1-14.3
Adult clients of state-funded alcohol/drug services†	11.7	4.0	2.1-19.4
Adult drug law violation arrests†	2.6	1.0	0.7-5.8
Individual birth-level exposures			
Maternal race			
Black	*8.5*	-	0-1
Hispanic	*7.9*	-	0-1
Native American	*10.2*	-	0-1
White	*70.0*	-	0-1
Substance exposure			
Amphetamines	*17.9*	-	0-1
Cannabis	*24.8*	-	0-1
Cocaine	*4.6*	-	0-1
Opioids	*47.6*	-	0-1
Alcohol	*5.0*	-	0-1
Late/no prenatal care	*26.4*	-	0-1
Public birth payment	*80.4*	-	0-1
Low birth weight	*19.2*	-	0-1
Maternal age	26.4	5.6	13-49
Infant gestational age	37.7	2.9	22-43
First born	*35.5*	-	0-1

The values that are percents are in italics to distinguish between means and percents.
*Averaged over the time period of the study (2006-2013).
†Rates per 1000 adults.

Table II. Results of BMA

Variables	$P(\beta \neq 0)$	EV	SD	Model 1	Model 2	Model 3	Model 4
Hospital Medicaid percent	100.0	0.23	0.05	0.24	0.23	0.25	0.23
Hospital no. of births	100.0	0.25	0.05	0.25	0.26	0.23	0.26
Hospital length of stay	100.0	−0.27	0.06	−0.26	−0.25	−0.32	−0.27
Hospital occupancy percent	100.0	0.29	0.06	0.30	0.30	0.28	0.30
Substance abuse deaths	15.3	0.02	0.05	-	-	-	-
Substance abuse services	1.9	0.00	0.02	-	-	-	-
Drug arrests	100.0	−0.29	0.07	−0.31	−0.31	−0.21	−0.31
Rural	73.3	0.19	0.13	0.25	0.26	-	0.26
Amphetamine exposure	100.0	0.94	0.06	0.95	0.93	0.96	0.94
Cannabis exposure	100.0	−0.49	0.06	−0.48	−0.49	−0.47	−0.52
Cocaine exposure	100.0	0.88	0.10	0.87	0.88	0.88	0.89
Alcohol exposure	0.0	0.00	0.00	-	-	-	-
Black	0.0	0.00	0.00	-	-	-	-
Hispanic	0.0	0.00	0.00	-	-	-	-
Native American	100.0	0.37	0.07	0.38	0.36	0.39	0.37
No/late prenatal care	100.0	0.29	0.05	0.29	0.29	0.29	0.30
Public insurance	100.0	0.54	0.06	0.55	0.52	0.55	0.53
Low birth weight	100.0	0.26	0.06	0.26	0.26	0.26	0.26
Maternal age	56.8	0.09	0.09	0.16	-	0.16	-
Gestational age	0.0	0.00	0.00	-	-	-	-
First born	29.9	−0.05	0.08	-	−0.16	-	-
No. of variables				14	14	13	13
BIC				−91 536.40	−91 535.35	−91 534.70	−91 534.38
Posterior probability				0.297	0.176	0.127	0.108

EV, model probability-weighted average β; *SD*, model probability-weighted SD.
$P(\beta \neq 0)$ is the probability the predictor is in the correct model.
The 4 best fitting models are presented based on the posterior probabilities and BICs.

Thus, 14 of the possible 20 variables were indicated to be included based on the BMA results.

Multilevel Logistic Regression Model Results

The multilevel random intercepts model was indicated as the model best fitting the data by its BIC (12 042.93), which was lower than the standard general linear model (12 091.40). Further, the intraclass correlation coefficient was 0.119 indicating that variance can be attributed to hospital-level differences.

Substance-exposed infants had increases in the likelihood of being reported to CPS when they were born in hospitals that had higher percentages of their revenue from Medicaid (OR, 1.25; 95% CI. 1.08-1.45) and had higher hospital occupancy percentages (OR, 1.43; 95% CI, 1.15-1.77). Conversely, substance-exposed infants were less likely to be reported to CPS when born in hospitals with longer average lengths of patient stay (OR, 0.72; 95% CI, 0.56-0.92) and located in counties with higher drug arrest rates (OR, 0.77; 95% CI, 0.63-0.95).

Infants exposed to amphetamines (OR, 2.58; 95% CI, 2.31-2.90) and cocaine (OR, 2.33; 95% CI, 1.91-2.83) had increased likelihoods of being reported and infants exposed to cannabis (OR, 0.62; 95% CI, 0.55-0.70) had decreased likelihoods of being reported to CPS. Infants whose mothers were Native American (compared with white; OR, 1.47; 95% CI, 1.27-1.70), had either late or no prenatal care (OR, 1.32; 95% CI, 1.18-1.47), and were older (OR, 1.16; 95% CI, 1.06-1.27) were more likely to be reported to CPS. Infants with low birth weight (OR, 1.32; 95% CI, 1.18-1.47) and whose births were paid for through public insurance (OR, 1.74; 95% CI, 1.54-1.98) also had increased likelihoods of being reported to CPS. The average number of births at the hospital and the rural location of the hospital were not significantly associated with CPS referral status. Full multilevel regression results as ORs are presented in the **Figure**.

Discussion

Our study identified key hospital-level and birth-level factors that are associated with the reporting of infants with diagnosed substance exposure to CPS. In terms of hospital-level factors, our findings indicate that hospitals that treat larger proportions of low-income patients, as indicated by payments via Medicaid, and hospitals that are busier, as indicated by higher occupancy rates, have increased likelihoods of reporting infants diagnosed with substance exposure to CPS. It is possible that these hospitals have specific policies in place with regard to reporting diagnosed prenatal substance exposure because births paid for with Medicaid have been shown to have higher rates of diagnosed prenatal substance exposure.[23] Decreases in the likelihoods of reporting to CPS were seen for hospitals that have longer average lengths of stay for their patients and are located in counties with higher rates of drug arrests. These findings indicate that certain characteristics of the type of hospitals where substance-exposed children are born are associated with increased likelihoods of those children being reported to CPS.

At the individual level, several key findings were made. First, consistent with the California study,[23] the type of

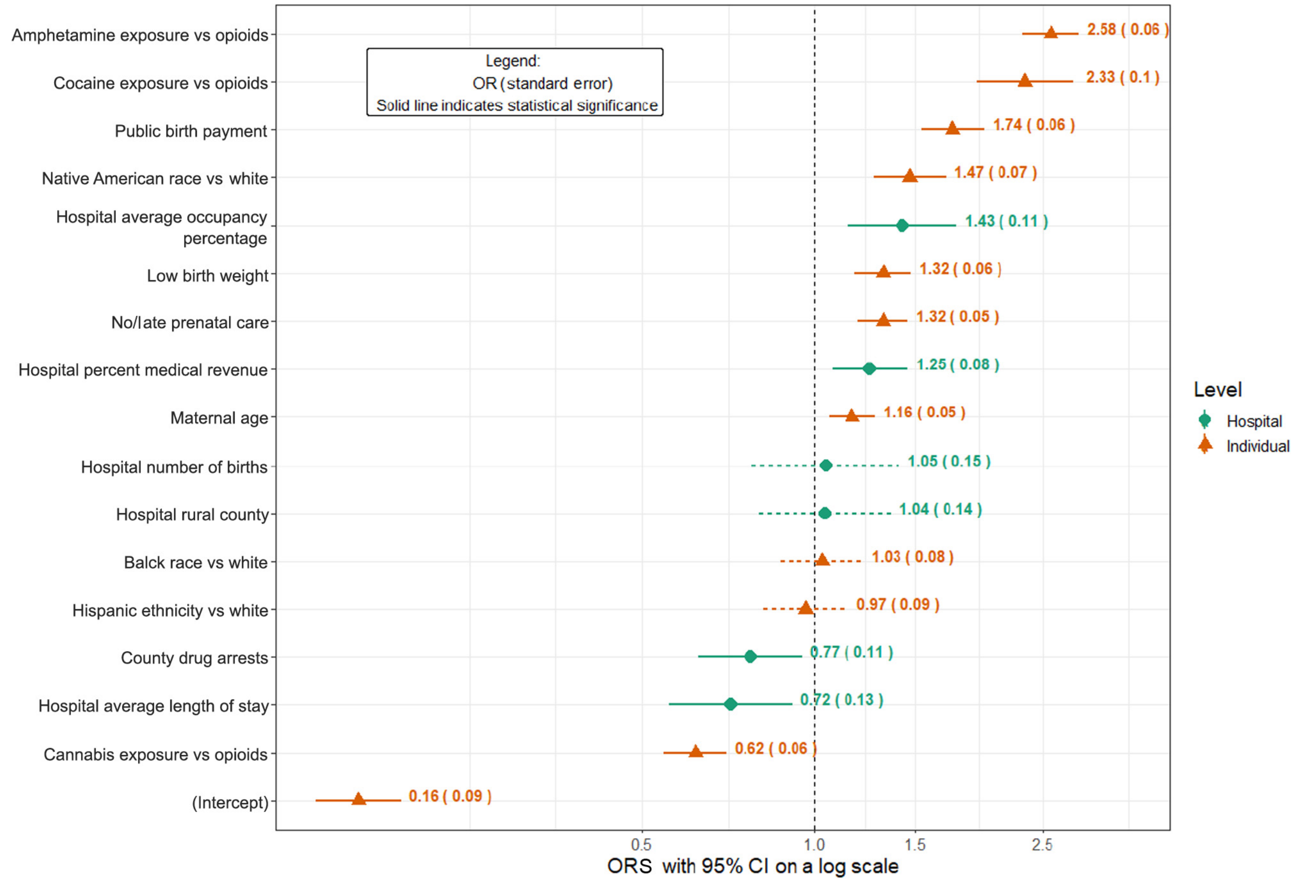

Figure. ORs of multilevel regression results of reports to CPS.

diagnosed substance exposure mattered with infants exposed to amphetamines and cocaine having increased likelihoods of CPS reports and cannabis-exposed infants had decreased likelihoods of being reported compared with infants diagnosed with prenatal exposure to opioids. This finding may, in part, be a reflection of Washington State's public support for the legalization of cannabis, which occurred in 2012. Further, 2 characteristics of infants at birth were associated with being reported to CPS: low birth weight, or less than 2500 g at term, and a public birth payment.

Second, 3 maternal characteristics were found to increase the likelihood of reporting to CPS: Native American race (compared with white), no or late prenatal care, and older age. Similar to the California study, infants of black or Hispanic mothers were no more likely than infants with white mothers to be reported to CPS. However, the California study did not include analyses on Native American infants, so we cannot make a comparison. The timing of prenatal care, specifically late or no prenatal care, increased the likelihood of CPS reports and possibly indicates the perceived importance of prenatal care to medical providers. We also find that infants born to older mothers have an increased likelihood of having a CPS report, perhaps indicating the perceived increased severity of a substance abuse problem among older mothers, compared with younger mothers, whose substance abuse may be associated with their youth.

The increased odds of children born to Native American mothers being reported to CPS may be a reflection of implicit biases of medical personnel. Research has identified that implicit bias against non-whites exists among many health care providers.[38] Similarly, the higher rates of diagnosed prenatal substance exposure for infants of Native American mothers may reflect the bias to test this population at higher rates than other racial and ethnic groups. Conversely, it is also possible that the results reflect an accurate account of a higher level of risk for this population in terms of maternal substance use during pregnancy and assessed risk by unbiased medical providers. If this is true, it is important to understand the historical context under which Native women live. Walters and Simoni note that "the behavioral health problems (eg, diabetes, alcoholism) of Native women are directly connected to their colonized status and to associated forms of environmental, institutional, and interpersonal discrimination."[39] Thus, if these results are an indication of a true higher risk for the children of Native American women, these results must be contextualized with an understanding of the historical trauma and high rates of interpersonal stressful events experienced by this population.[40] Further analysis of this population is needed to fully discern the needs and biases experienced by Native women in regard to prenatal substance exposure.

These results contribute to the broader discussion regarding how women are screened for substance use during pregnancy and birth. Both the American Academy of Pediatrics[41] and the American College of Obstetricians and Gynecologists[42] have advocated for universal screening procedures to identify pregnant women with substance use concerns to refer and engage them in treatment. Until these universal screening procedures are implemented uniformly, there is uncertainty regarding the role that bias may be having on these results.

Although federal and state policies mandate that health professionals report prenatal substance exposure to CPS, it is unclear how states and CPS should respond to these reports. Previous research using the same dataset in Washington state found that only 13.3% of infants diagnosed with prenatal substance exposure were removed by CPS from their families during the neonatal period.[43] However, some states have taken more punitive approaches to diagnosed prenatal substance exposure, including the passage of legislation to prosecute mothers who use illicit drugs during pregnancy.[41] Such punitive actions may influence medical providers' decisions to report prenatal substance exposure infants to CPS. Future research should investigate further what services and treatments are provided to mothers after a report to CPS is made and if they are in line with the American Academy of Pediatrics' recommendations[41] to increase access to treatment instead of punishing mothers.

Although this study provides new information about hospital-level and individual-level characteristics related to CPS reporting of diagnosed prenatal substance exposure, there are some limitations. First, we relied on ICD-9 codes to assess substance exposure, which are standardized codes for diagnoses but are not without limitations. Although it is likely that our estimates are attenuated, it is unclear whether hospitals are applying these diagnostic codes in consistent ways. Relatedly, some of the ICD-9 codes did not specify a specific substance, requiring the imputation of this information. We argue that this is more beneficial than keeping a diagnosis without a substance type specified as it provides more information than an NOS category and keeps the observations in the model. Further, we ran models including the NOS category without imputation and a model list-wise deleting observations with the NOS diagnosis. The models were similar in terms of effect sizes and directions, further supporting our use of the imputation.

Second, our analysis is unable to account for possible physician and hospital screening bias. If there are differences in screening based on race or other characteristics, this could result in differences in reports to CPS that we are unable to account for.

Third, there are some hospital-level characteristics that our study does not account for, including the presence of Child Protection Teams at the hospitals and previous interactions by the hospital with the child welfare system. Factors such as these may also be associated with reports to CPS.

The age of our data is another limitation given the rapid increase in opioid use during the most recent years, which we might expect to alter our findings. Finally, it is unknown how generalizable the findings are to other states given the differences of how prenatal substance exposure is treated in different states, but these results suggest that hospital-level differences in reporting should be explored in future research.

The variation in reporting practices based on hospital-level factors indicates that reports to CPS are not made in a standardized way. Results of these differences present opportunities for targeted training and prevention efforts. Specifically, improved policies targeted at the hospital level, especially in terms of clear guidelines for when a referral to CPS is appropriate, may be necessary to reduce differences at this macro level. ■

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Appendix 1

ICD-9 codes used to identify substance exposure diagnoses

Substance abuse categories	ICD-9 codes
Alcohol-induced mental disorders	291
Drug-induced mental disorders	292
Alcohol dependence syndrome	303
Drug dependence	
Opioid type dependence	304.0
Sedative, hypnotic, or anxiolytic dependence	304.1
Cocaine dependence	304.2
Cannabis dependence	304.3
Amphetamine, other psychostimulant dependence	304.4
Hallucinogen dependence	304.5
Other specified drug dependence	304.6
Combinations of drugs dependence	304.7, 304.8
Unspecified drugs dependence	304.9
Nondependent abuse of drugs	
Alcohol abuse	305.0
Cannabis abuse	305.2
Hallucinogen abuse	305.3
Sedative, hypnotic, or anxiolytic abuse	305.4
Opioid abuse	305.5
Cocaine abuse	305.6
Amphetamine or related sympathomimetic abuse	305.7
Antidepressants type abuse	305.8
Other, mixed, or unspecified drug abuse	305.9
Toxic effect of alcohol	980.0
Pregnancy and childbirth	
Drug dependence	648.3
Suspected damage to fetus from drugs	655.5
Noxious influences affecting fetus or newborn	
Alcohol/fetal alcohol syndrome	760.71
Narcotics	760.72
Hallucinogenic agents	760.73
Cocaine	760.75
Drug withdrawal syndrome in newborn	779.5

Appendix 2

As noted, the exposure variable in this study was coded using the most frequent infant substance exposures (with at least 500 exposure births) with the largest category, opioids, serving as the referent category. Several subjects (37%) were categorized as dependence or exposure (NOS). Given the lack of clinical relevance to such a category, we inferred the actual exposure to these levels using the 'missForest' algorithm from the eponymous R package.[1,2] This algorithm has been shown to perform well as compared to multiple-imputation approaches.[3] The nonparametric nature of the algorithm is also less computationally intensive than multiple imputation algorithms—a key consideration given the relatively large number of records in our study.

We began our imputation process by proceeding from the assumption that some nontrivial portion of the subjects classified as Dependence or Exposure NOS did not have exposure to any of the substances in the variable described. Rather, they had exposure to one of our excluded categories of tobacco, antidepressants, hallucinogens, and benzodiazepines. In the interest of being conservative in our estimation of the actual exposure values for the category, we expanded the possible drug categories to include these previously excluded categories. In other words, instead of forcing the model to pick between the 5 categories, we made the model pick between 10. Although this approach would likely decrease our potential sample size (ie, some of the subjects classified as Dependence or Exposure NOS would certainly end up categorized as one of these previously excluded categories), we found this preferable to erroneously including a low-risk subject (ie, a subject exposed to one of the low risk drugs) in our final sample.

As implemented in this study, the 'missForest' algorithm only predicted one type of exposure per child. Because the observed exposures may involve multiple substance types per child, the exposure distribution of the inferred exposures are not directly comparable to the observed exposures. In bivariate analyses predicting our outcomes of interest, the observed vs inferred exposures produce similar point estimates. The only substantive difference between these models is that the inferred exposures produce smaller standard errors due to the larger number of observations in each category. The final set of possible exposure categories was opioids (n = 5927 [48.2%]), cannabis (n = 2975 [24.2%]), amphetamines (n = 2212 [18.0%]), cocaine (n = 582 [4.7%]), and alcohol (n = 612 [5.0%]).

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