# The Impact of Substance Abuse in Tennessee:
# The Relationship between Low Birth Weight and Substance Use During Pregnancy

Working Paper

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**Abstract**

The opioid crisis is a rampant issue affecting North America with impacts that are only beginning to be fully understood. Neonatal abstinence syndrome is a tragic birth outcome newborns face as a result of withdrawal from substance use by the mother during pregnancy. NAS has become a rising concern throughout the United States and especially in Tennessee. Our study examines the percentage of low birth weights as a result of NAS among each county and between the years 2013 to 2016 to further understand existing impacts of the opioid crisis. After controlling for other risk factors, our results indicate that NAS results in an additional burden to healthcare resources by increasing the percentage of low birth weight from about 5.95% to 15.61%. Birth weight is generally the most substantial indicator of the infant's health over the first year of its life and increases in low birth weight babies will continuously escalate future healthcare cost.

**Keywords:** Neonatal abstinence syndrome, low birth weight, opioid crisis, two-stage least squares,

## Introduction

Within the first ten years into the millennium, North America experienced an exponential rise in the use of opioids as a result of the over-prescription of powerful opioid pain relievers in the 1990s, which led to them becoming one of the most prescribed classes of medications in the United States (U.S. Department of Health & Human Services). As a result of this dubbed crisis, devastating increases in drug death rate by overdose, the spread of communicable diseases, and the economic burdens are just a few of many multifactorial effects of the crisis. The opioid crisis has since emerged as one of the worst drug crises in American history with more than 33,000 reported death overdoses in 2015 alone which was virtually equal to the number of deaths from car crashes and more than the amount of deaths from gun homicides (Ingraham, 2016).

The opioid crisis of North America has also affected Canada and further action is being taken to fully understand its impacts to Canada. As Canadian healthcare is universal, it is important for tax paying Canadians to understand such impact as the extra resources from substance use during pregnancy affects all Canadians.

For a long time now, it has been known that an infant's birth outcome is a result of the mother's health and environment before and during her pregnancy. When assessing neonatal morbidity and mortality, birth weight is generally the most significant indicator of the infant's health over the first year of its life.

Low birth weight (LBW, <2,500 grams) is used amongst many scholars and researchers when observing neonatal health outcomes due to the necessary requirement for neonatal care, extended hospital stay and the increased likelihood of necessary re-hospitalization within the first 12 months of life. Due to its relevance to infant health status and additional demand for healthcare as a result of its complications, there exists abundant analysis on determinants of low birth weight.

Existing studies have classified relevant factors related to the risk of LBW outcomes, some of which may include: demographic characteristics (i.e., mother's race, age, education level, socio-economic status, and access to prenatal care) and ongoing maternal exposures to an array of substances including tobacco, alcohol and illicit drugs.

The purpose of the present study is to examine, on a district-level population, the correlation between LBW rate and neonatal abstinence syndrome (NAS) which is the horrific display of withdrawal syndrome infants face after birth caused by in utero exposure to drugs of dependence (Hamdan, et al., 2017) over the past 4 years[1] in Tennessee in order to analyze the most up-to-date direction of the opioid crisis. Tennessee ranked third for states in the highest amount of prescription opioids in the USA in 2016. Distinctively, we wish to examine the amount of LBWs between various health districts in Tennessee as a

[1] Effective January 1, 2013, all cases of NAS diagnosed among Tennessee resident births should be reported to the Tennessee Department of Health at the time of diagnosis (https://www.tn.gov/health/nas.html)

result of NAS in order to further interpret the existing burdens to local health districts from the opioid crisis.

In addition, a recent study by Milliren, Gupta, Graham, Melvin, Jorina, & Ozonoff (2018) which falls under the timeline we wish to observe (2013 to 2016) examine recent population of NAS newborns admitted to pediatric hospitals, hospital variation in pharmacologic treatment, and the effect of treatment on resource use during neonatal hospitalization, including length of stay (LOS), readmission, and cost -of-living adjusted hospital costs. By using information from hospitals in the Pediatric Health Information System, neonates with NAS were compared to those without to observe differences in socioeconomic, clinical characteristics and hospital resource use. The results indicated that NAS neonates had longer length of stay (18.7 vs 2.9 days; P= .004), average costs per admission were 10 times higher for neonates with NAS ($37 584 vs $3536; P= .003). 70% of neonates were treated pharmacologically with wide variation in hospital rates of pharmacotherapy. Total costs for pharmacologically-treated neonates with NAS were over 2 times higher ($44 720 vs $20 708; P = .002) than neonates with NAS treated without pharmacotherapy. As mentioned, this study is fairly recent and falls under our timeline and gives evidence on the hypothesis of our study.

**Review of the literature**

There exists an extensive amount of literature on the impacts of substance use during pregnancy, its additional burden to the healthcare resource, and the risks it carries for neonatal complications, specifically low birthweight. Joyce, Racine , & Mocan, N. (1992) investigated the dramatic rise in low birthweight in New York City between 1980 and 1989 by using a pooled time-series cross-section of live births. Particularly, Joyce theorized that the explosion in the use of cocaine during the 1980s is to blame for the surge in LBW at the time. The data used included all singleton live births to Black non-Hispanics, White non-Hispanics, and Hispanic residents of New York City between 1980 and 1989 using on 30 health districts within New York City for 10 years. The study used minimum chi-squared methods model and the proportion of LBW is as follows;

$$LBjt= \gamma_1+\mu_j+\beta_k X_{kjt}+e_{jt},$$

where LBjt is the proportion of LBW births and Xkjt, a vector of the five health inputs: the proportion of births to women out-of-wedlock, with inadequate care, with four or more previous live births, and women who used tobacco and consumed drugs during pregnancy.

The findings of Joyce et al. (1992) provide the importance of a substance abuse variable in accounting for a large degree of the change in LBW among the Black population during this period. The

high estimation describes almost 80% of the calculated change in LBW to the effect of substance abuse while low estimate assigns substance abuse 28% of the total change. The high estimation is based on coefficients from the model using instrumented OLS with time dummies for blacks and Hispanics, and non-instrumented OLS with time dummies for whites. The low estimation was based on coefficients from the model using non-instrumented OLS with time and district dummies. In conclusion, it was found that the independent effect of illicit substance use varied substantially by race with little effect demonstrable among Whites.

Patrick, Schumacher, & Benneyworth et al. (2015) probed the frequency of Neonatal Abstinence Syndrome and antepartum maternal opioid use on a national level to characterize trends in national health care expenditures associated with NAS between 2000 and 2009. By performing a retrospective, serial, cross-sectional analysis of a national sample of newborns with NAS and common neonatal morbidities such as incidence of seizures, respiratory symptoms, feeding difficulties, and low birthweight from data obtained by the Kids' Inpatient Database (KID), Patrick et al. (2012) performed statistical comparisons between infants with NAS discharges vs discharges for all hospital births. For the purpose of our study, we take distinctive interest in the low birthweight outcomes and the additional expenses as a result of NAS. The findings indicate that when compared with all other hospital births, newborns that suffer from NAS were significantly more likely to have low birthweight (19.1%; SE, 0.5%). It is also important to note that the rate of newborns diagnosed with NAS increased from 1.20% to 3.39% per 1000 hospitalization births per year. Mean hospital charges for newborns with NAS increased from $39 400 to $53 400 with Medicaid as the primary payer for the majority of hospital charges. The findings of this study provide further evidence of growing social and economic burdens as a result of the rise of opioid use. As this study is relatively recent when compared to our time series, we wish to study the effects on the proportion of low birth weights that are a result of NAS (as done by Joyce et al., 1992) which can be used to observe the burden the healthcare industry currently faces when implementing our model.

As mentioned, the increasing rate of NAS cases in The United States is a result of the ongoing opioid epidemic which we believe is beginning to contribute to instances of neonatal morbidity, specifically low birthweight. Patrick, David, Lehmann, & Cooper (2017) analyze diagnostic and demographic data for hospital discharges between 2009-2012. Kids' Inpatient Database is used once again, as well as the Nationwide Inpatient Sample in order to understand recent changes in NAS and its variances geographically. Their findings indicate that on a national level, NAS incidence increased nationally from 3.4 to 5.8 per 1000 hospital births. When comparing state level incidence rates, the highest rates where Kentucky, Tennessee, Mississippi and Alabama for the East South Central Division. Aggregate hospital charges for NAS increased from $732 million to $1.5 billion with 81% covered by state Medicaid programs

in 2012. This study provides even further evidence of increasing healthcare costs of this epidemic and it also inspired us to choose the state of Tennessee for our study.

The opioid crisis of North America has also affected Canada and further action is being taken to fully understand its impacts to Canada. As Canadian healthcare is universal, it is important for tax paying Canadians to understand such impact as the extra resources from substance use during pregnancy affects all Canadians. Filteau, Coo, & Dow (2018) study the associated healthcare resource utilization from neonatal abstinence syndrome in Canada (all provinces and territories excluding Quebec). By performing secondary analysis with the data provided from all hospitals and access to the Canadian Institute for Health Information discharge abstract database the study examined incidence, hospital beds occupied per day, length of stay (fiscal 2003-2014), hospital costs, and demographic features. The findings indicated a tripling of NAS incidence (1.8-5.4 per 1000 live births), equipped with an average annual increase of 0.33 per 1000 live births. On a provincial level, NAS incidence between 2.7 (Alberta) to 9.7 (New Brunswick) per 1000 live births. Between 2010 and 2014 total and mean per-patient costs rose from $15.7 to $26.9 million CAD and $14.629 to $17,267 CAD, respectively. Mean length of stay was 14.4 days in 2003 and 14.8 in 2014, and beds occupied per day rose from 19.7 in 2003 to 69.4 in 2014. This study gives interesting variables used for hospital utilization calculation and only exemplifies the burden NAS is towards Canadian Healthcare.

Ariadna Forray (2016) performs an empirical study on the effects of substance use during pregnancy. We thought that it is imperative to perform a review on empirical literature as well. Forray examines literature on prenatal use of tobacco, alcohol, cannabis, stimulants, and opioids, including effects to both maternal and fetal health outcomes. For the purpose of this study, we will share her findings on relevant information to our model and analytical framework. Smoking during pregnancy was found to cause adverse effects on birth outcomes, including (but not limited to) miscarriage, low birthweight, placental abruption, preterm birth, and increased infant mortality. Similar to the other literature we have mentioned, opioid use in pregnancy is correlated with greater risk of low birth weight, respiratory problems, third trimester bleeding, toxemia and morality.

**The Model**

We wish to reanimate the estimation model of LBW as a result of health inputs and prenatal drug use as done by Theodore Joyce et al. (1992). We believe that we can transfer the theoretical models to describe impacts of the opioid crisis in Tennessee by observing proportions of Low Birth Weight per county. However, for prenatal drug use we will be using Neonatal Abstinence Syndrome to observe impacts as done by Filteau et al. (2018). Our model looks to specify the impact of substance abuse. We wish to observe the aggregated impacts of low birthweight (<2,500 grams) as a result of substance use during pregnancy.

The vector containing our explanatory variables can be seen below:

$$X_{jt} = NAS_{jt} + TOBACCO_{jt} + WEDLOCK_{jt} + TEENBIRTH_{jt} + UNINSURED_{jt} + TANF_{jt} \quad (1)$$

Our multivariable linear regression model will take the form:

$$LBW_{jt} = \alpha_j + \beta_k X_{jt} + \varepsilon_{jt} \quad (2)$$

where,

k = 1, 2, 3, 4, 5, and 6.

(k,j,t) is the number of coefficients, time and district specific effects, respectively. ($\alpha_j$) is the fixed or random effects adjustment for the time- and district-specific effects. $LBW_{jt}$ is the percentage of babies born with a birth weight of <2,500g. $X_{jt}$ is a vector of the six explanatory variables: $NAS_{jt}$ is the proportion of infants born with clinical signs of Neonatal Abstinence Syndrome, $TOBACCO_{jt}$ is the percentage of mothers that indicated using tobacco during pregnancy, $WEDLOCK_{jt}$ is the percentage of the live births occurring to women who at the time of delivery where unmarried, $TEENBIRTH_{jt}$ is the percentage of births per 100 female population, ages 15-19, $UNINSURED_{jt}$ is the percentage of the population under age 65 that has no health insurance coverage, and Temporary assistance to needy families ($TANF_{jt}$) is the percentage of children under 18 receiving Temporary Family Assistance (TFA) benefits for the designated year in a county within Tennessee.

As mentioned, Neonatal Abstinence Syndrome is a result of substance addiction from the mother being transferred to the fetus during pregnancy. The empirical findings of Ariadna Forray (2014) state a relationship between birthweight and smoking by the mother, which is why we believe it is relevant to our model. Births are assigned to the county in which the mother resides in, regardless of which county the actual birth took place. Both biological and sociocultural factors, as well as lifestyle decisions made by adolescents, combine the risk of delivering a low birth weight infant. Health insurance is usually an indicator of socioeconomic status in the United States since, where uninsured in most cases usually indicates low socioeconomic status of the mother. We believe that the incidence of uninsured births contributes to a positive increase in LBW occurrence. TANF eligible children include those in families where the parents are enrolled in the employment focused, time limited assistance program.

We predict that our explanatory variables will be positively associated with low birth weight and therefore, show the potential negative impact of social and health behaviors on low birth weight. By observing the discoveries of Valerie E. Whiteman et al., Ariadna Forray, and S W Patrick et al, we hypothesize that substance use during pregnancy (specifically opioids) will have a significantly positive correlation on the birth weight of a baby.

**Methodology**

For estimation we used STATA/SE 15.1. Our model takes form of a linear pooled cross-sectional time-series model (panel) as the OLS model for low birthweight used in Joyce et al. (1992). As we move towards our regression analysis, there are some things to consider. Assuming that the standard deviation of the error term is constant over all values and that the regressors are not correlated with the errors seems invalid and therefore heteroscedasticity and endogeneity raises concern. It should be noted that the traditional OLS method has two critical drawbacks. It cannot control for county-specific factors and it assumes the intercept value of the counties are the same. Thus, we conduct additional tests for two panel estimation methods, which take into consideration the specific heterogeneity of the counties, to determine whether the OLS characteristics are questionable.

We run the fixed-effects (FE) model to allow for a limited form of endogeneity since it is acceptable that the $\alpha_j$ in equation (2) be correlated with the regressors $X_{jt}$. Having varying intercepts for each county is allowed in the fixed effects model when adding dummy variables that control county-specific effects (Cameron, Adrian  Collin, 2009). To determine whether these dummies belong to the model, we conduct an F test using the STATA command *testparm.* In addition to the F test, we conduct various diagnostic tests to determine the presence of heteroscedasticity, serial correlation, panel-specific autocorrelation, and cross sectional dependence in the fixed effects model (FE).

In the random-effects (RE) model, it is assumed that $\varepsilon_{jt}$ is not correlated to any explanatory variable $X_{jt}$ in equation (2). Since $\alpha_j$ $is$ assumed to be completely random we can make a further assumption implying that $\alpha_j$ is uncorrelated with the regressors. The RE estimator uses both between and within variation in the data and has special cases of pooled OLS ($\widehat{\theta_\iota}$ = 0) and within estimation ($\widehat{\theta_\iota}$ = 1).

When comparing FE and RE, in order to determine which estimation method is feasible we conduct the Hausman test for specification (1978). FE is the preferred estimation method when the following observations are present; measurement error, underreporting, and unobserved heterogeneity. We would favour a FE estimation since no assumptions are made regarding the distribution of the effects, and even if the effects and/or underreporting are correlated with the regressors its coefficients remain consistent. However, with the FE estimator we lose cross-district heterogeneity. Given the inequality in NAS across counties we suspect cross-district heterogeneity to be an important source of variation. Thus, we will use the Hausman test to ascertain whether a random effects estimator is feasible [Hausman (1978); Hausman and Taylor (1981)].

A recent study has found that when comparing counties from eastern Tennessee to other counties, cases of NAS were more prevalent from a result of numerous maternal, infant, and delivery characteristics when compared to non-NAS births (Paul Campbell Erwin et al., 2018). The general problem of endogeneity arises within a system where NAS is said to influence the error term (Diagram 2) and cause inconsistencies

of the usual OLS estimates. By contrast, in Diagram 1, we observe a simple regression model where the exogenous regressor arises outside the system and is unrelated to the error term. Endogeneity bias is the inconsistency of $\hat{\beta}$, where the bias does not disappear asymptotically. In the following path diagrams, $\chi$ is NAS, $y$ is LBW, and $\mu$ is the error term.

Diagram 1: Simple Model

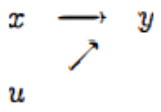
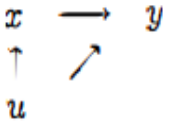
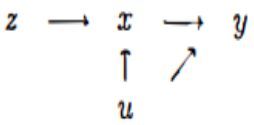



Diagram 2: Endogeneity




The IV approach provides a solution to endogeneity and we believe that instrumental variable (IV) methods like two-stage least squares (2SLS) and limited-information maximum likelihood (LIML) are required to obtain unbiased estimates of $\beta$, the marginal effect of neonatal abstinence syndrome on low birth weight. We introduce four instrumental variables; a dummy variable for eastern Tennessee (East = 1, otherwise = 0), the number of drug deaths per 100,000 residents, the percent of children under age 18 living with an income below the official poverty threshold, and the percentage of reported child abuse victims younger than age 18. Each instrument accounts for county and year as an instrument for NAS. The deviation in instrumental variables, $z_k$, do not lead to variations in y (except indirectly via $\chi$), but do show a relationship with variations in $\chi$. This leads to the following path diagram, where $z_k$ is the instrumental variable and k = 1, 2, 3, and 4.

Diagram 3: IV Approach




A crucial assumption is that the instrumental variable estimator $\widehat{\beta_{IV}}$ is consistent for $\beta$ assuming that the instrument $z$ is uncorrelated with the error $\mu$ and correlated with the regressor $\chi$.

Drug deaths per 100,000 residents measure the prevalence of illicit opioid activity between counties which will help with the endogeneity concerns we have within our model. The availability of opioids should have a strong correlation with the use of opioids during pregnancy (which is the cause of NAS). This also works because the death rate of drug use nor location do not have a direct effect on birth outcomes, making it exogenous to the model overall.

NAS is much more prevalent in eastern Tennessee as cited in (Paul Campbell Erwin et al., 2018). With these findings, we use a dummy variable to determine the relationship between eastern Tennessee counties and the variation in the percentage of NAS. As observed in Table 1, our instrument variables have a moderate correlation with NAS [34.21%, 64.38%, 45.82%, and 32.46%] and no direct effect on birth outcomes and therefore, are exogenous to the model.

Since our IV estimation uses more than one instrument, we can consider the joint correlation of NAS with the several instruments. Two feasible measures of this correlation are the R-squared from regression of the endogenous regressor NAS on the several instruments (Appendix B -Table B.2.2.1), and the F statistic for test of overall fit in this regression. Low R2 or F values can be an indicator of weak instruments. If the instruments add minimal additions to explaining LBW after controlling for the exogenous regressors, then the instruments are weak.

Table 1: Correlation Matrix of the Endogenous Variable (NAS) on the Instrument Variables

```
. pwcorr NAS DrugDeathsIV DummyEastTennessee RepChildAbsCases ChildPov
```

| | NAS | DrugDe~V | DummyE~e | RepChi~s | ChildPov |
|---|---|---|---|---|---|
| NAS | 1.0000 | | | | |
| DrugDeathsIV | 0.3421 | 1.0000 | | | |
| DummyEastT~e | 0.6438 | 0.2292 | 1.0000 | | |
| RepChildAb~s | 0.4582 | 0.3172 | 0.2814 | 1.0000 | |
| ChildPov | 0.3246 | 0.0831 | 0.1469 | 0.4734 | 1.0000 |

From Table 1, we note that the gross correlations of instruments with the endogenous regressor NAS are moderate. This will lead to efficiency loss using IV compared to OLS, but the correlations are not low enough to immediately flag a problem of weak instruments. Therefore, we can continue with these instruments.

**Data Sources**

Data for this study came from three sources. The first source was the KIDS COUNT data center for neonatal abstinence syndrome (NAS), births to unmarried females (Wedlock), and temporary assistance to needy families (TANF). The instrument variables, the percent of children under age 18 living with an income below the official poverty threshold (ChildPov), and the percentage of reported child abuse victims younger than age 18 (RepChildAbs), were also found utilizing the KIDS COUNT data center. To collect the following variables we had to specify by county for Tennessee, then subsequently select the corresponding indicators, including Economic Well-Being, Family and Community, Health, and Safety & Risky Behaviors. For this study we used the Health Indicator [sub-indicator: Birth Outcome] to find NAS, Family and Community Indicator [sub-indicator: Family Structure] to find Wedlock, Economic Well-Being

Indicator [sub-indicators: Public Assistance and Poverty] to find TANF and ChildPov, respectively, and the Safety & Risky Behaviors Indicator [sub-indicator: Child Abuse and Neglect] to find RepChildAbs.

The average percentage of baby born with low birth weight in Tennessee was 8.875% between 2013 and 2016. Since the average standard deviation of 1.257 is smaller than the mean, this indicates that more of the low birth weight data is clustered about the mean. Neonatal abstinence syndrome (NAS) is the only explanatory variable where the standard deviation is larger than the mean. This indicates that the NAS data points are more spread out over a wider range of values, thus signifying that the average variation around the mean is large.

Table 2: Summary statistics for the low birth weight regression equation

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | N | mean | sd | min | max |
| LBW | 380 | 8.875 | 1.257 | 5.700 | 12.50 |
| NAS | 380 | 1.838 | 1.981 | 0 | 11.40 |
| WEDlock | 380 | 43.39 | 8.289 | 10.30 | 70.70 |
| TeenBirth | 380 | 5.152 | 1.166 | 1.100 | 9.600 |
| Uninsured | 380 | 17.04 | 1.981 | 8 | 22 |
| TANF | 380 | 1.399 | 0.596 | 0.127 | 4.499 |
| Tobacco Use | 380 | 22.69 | 7.086 | 2.998 | 43.55 |
| Number of county | 95 | 95 | 95 | 95 | 95 |

A second source of data was provided from the County Heath Rankings & Roadmaps program, consisting of Tennessee rankings data for individual years available for download in an excel workbook. Since this was a four year study, we downloaded four excel workbooks and collected the following data; the percentage of live births with low birth weight (LBW), percentage of births from females ages 15-19 (Teen Birth), and the percentage of the population under 65 without health insurance (Uninsured).

The Tennessee Department of Health provided us with an aggregated dataset from https://hit.health.tn.gov/HIT_OIT/BirthOutcomeQuery.aspx with 2016 included, which at the time of this study, was not available to the public. Although many of the variables provided to us were not significant to our model we chose to use the tobacco use during pregnancy data and replaced our old smoking during pregnancy variable from the KIDS COUNT data center. The new data was acquired to attempt to increase the accuracy of our estimation methods since much of the data available to the public is suppressed or rounded up. With the new data provided, our data quality is much more precise, therefore, our model is more accurate.

The final source was the “Data Dashboard”, an interactive data query tool administered by the Tennessee Department of Health provided us with drug death rates per county between the observed years.

This indicator includes all overdose deaths, regardless of intent (e.g., unintentional, suicide, assault, or undetermined). However, this figure does not include deaths related to chronic drug use, deaths due to alcohol and tobacco, and deaths that occurred under the influence of drugs.

From observing Table (3), the regressor model shows that wedlock has the strongest significance with low birth weight at 46.04% as well as the most significant relationship in the model with a significance of 59.14% with teen birth. On the other hand, the figures with the lowest significance with LBW are NAS and TobaccoUseDuringPreg. It is interesting to note that TobaccoUseDuringPreg is positively correlation with every figure except LBW. This could be due to the use of multiple datasets, which collected data using different methodologies. Hence, we suspect that multicollinearity is not present in our model since no relationships between explanatory or predictor variables have extremely significant correlations.

Table 3: Correlation matrix for the low birth weight regression model

```
. pwcorr LBW NAS TobaccoUseDuringPregancy TeenBirth WEDlock  Uninsured TANF
```

| | LBW | NAS | Tobacc~y | TeenBi~h | WEDlock | Uninsu~d | TANF |
|---|---|---|---|---|---|---|---|
| LBW | 1.0000 | | | | | | |
| NAS | 0.0282 | 1.0000 | | | | | |
| TobaccoUse~y | -0.0303 | 0.3465 | 1.0000 | | | | |
| TeenBirth | 0.2909 | 0.0266 | 0.3670 | 1.0000 | | | |
| WEDlock | 0.4604 | 0.0129 | 0.2469 | 0.5914 | 1.0000 | | |
| Uninsured | -0.1256 | 0.0983 | 0.3238 | 0.3965 | 0.1355 | 1.0000 | |
| TANF | 0.3661 | -0.0825 | 0.1297 | 0.4105 | 0.4945 | 0.1142 | 1.0000 |

**Results**

Table B.1.1 in Appendix B contain the diagnostic test results for the twelve cases relevant to our panel-data model: fixed effects and time-effects dummies, fixed effects and cross sectional dependence, fixed effects and groupwise heteroscedasticity, fixed effects and serial correlation, random effects or OLS, random effects and serial correlation, random effects and cross sectional dependence, random effects and overidentifying restrictions test, ordinary least squares (OLS) and heteroscedasticity, serial correlation in the panel-data model, fixed effects or random effects, and the presence of unit roots. We test for all these cases and provide the adjusted corrections in our final results, which are reported in table (4).

From these diagnostic tests, we observed that the Wald test suggested heteroscedasticity is present in the fixed effects model, the Breusch-Pagan LM-test suggested random effects over OLS, but suggested OLS when using an adjusting version (xttest1 command), the LM and Baltagi-Li (1995) test for first-order serial correlation suggested that autocorrelation is present in the random effects model, the Breusch-Pagan/Cook-Weisberg test for heteroskedasticity suggested homoscedasticity is present in the OLS model, the Wooldridge test for autocorrelation concluded the data does have first-order autocorrelation, and the Hausman test suggested fixed effects.

Due to group wise heteroscedasticity in the fixed effects model, we use the heteroskedasticity-robust standard errors command to correct the disturbance. From observing the three serial correlation tests for the fixed effects model, two indicate that the fixed effects model might be free of serial correlation. Therefore, we can suspect autocorrelation, but in order to confirm we will need to conduct more tests. However, with a large N (95), small T (4) panel dataset, autocorrelation should not be that relevant, whereas heteroskedasticity might be a greater concern.

We conduct two versions of the Breusch-Pagan LM-test, where the command xttest1 is an extension of xttest0. The purpose of the extension, xttest1, is that it presents several specification tests for balanced error component models. From this extension, we determine that serial correlation in both the adjusted and unadjusted version of the LM tests cause the adjusted version of the tests for random effects to modify its conclusion and fail to reject the null hypothesis. Thus, the adjusted version of the tests for random effects ALM(Var(u)=0) suggests the OLS method over random effects. Within the same test 'xttest1', we observed that first-order serial correlation was present in both the unadjusted and adjusted versions of the LM tests for serial correlation. Therefore, the adjustment of the test did not change the rejection of the null hypothesis.

The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity indicates that the errors are homoscedastic since p = 0.3301, even though the test for groupwise heteroscedasticity for the FE model had heteroscedastic errors.

Next, we carried out the Wooldrigde auto correlation test (2002) of a linear panel-data model. Since autocorrelation causes the standard errors of the coefficients to be smaller than they actually are, this test is essential because accuracy is critical in order to implement effective policy. One advantage of this test is that it does not impose a choice between a fixed effect and a random effect model. Therefore, we note (Prob>F= 0.0111), a rejection of the null hypothesis, which implies that the errors are correlated and there is a presence of first order autocorrelation.

Our regression results, as seen in Table 4, will explore the significance and accuracy of our model using five estimation methods; ordinary least squares (OLS), fixed effects (FE), random effects (RE), two stage least squares (2SLS), and limited information maximum likelihood (LIML).

Table (4): Low birth weight regressors to obtain heteroscedasticity-robust standard errors

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| VARIABLES | OLS | FE[a] | RE[a] | 2SLS | LIML |
| NAS | 0.0721** | 0.0241 | 0.0595* | 0.1532*** | 0.1561*** |
| | (0.0283) | (0.0562) | (0.0321) | (0.0425) | (0.0433) |
| TobaccoUseDuringPreg | -0.0295*** | -0.0316** | -0.0320*** | -0.0382*** | -0.0385*** |

| | | | | | |
|---|---|---|---|---|---|
| | (0.0086) | (0.0150) | (0.0095) | (0.0091) | (0.0091) |
| WEDlock | 0.0526*** | 0.0114 | 0.0378*** | 0.0521*** | 0.0521*** |
| | (0.0095) | (0.0091) | (0.0093) | (0.0095) | (0.0095) |
| TeenBirth | 0.1621** | -0.0213 | 0.1936* | 0.1745** | 0.1750** |
| | (0.0686) | (0.3613) | (0.1010) | (0.0692) | (0.0692) |
| Uninsured | -0.1338*** | -0.0137 | -0.1131*** | -0.1354*** | -0.1355*** |
| | (0.0297) | (0.0785) | (0.0387) | (0.0293) | (0.0293) |
| TANF | 0.3965*** | 0.3910 | 0.4370*** | 0.4258*** | 0.4269*** |
| | (0.0935) | (0.2676) | (0.1382) | (0.0955) | (0.0957) |
| Constant | 8.0212*** | 8.8505*** | 8.1673*** | 8.0102*** | 8.0098*** |
| | (0.4570) | (1.8339) | (0.6397) | (0.4487) | (0.4487) |
| Observations | 380 | 380 | 380 | 380 | 380 |
| R-squared | 0.3070 | | | 0.2930 | 0.2920 |
| Number of county | | 95 | 95 | | |
| County effects | | Yes | | | |
| R2 within | | 0.0259 | 0.0160 | | |
| R2 between | | 0.252 | 0.468 | | |
| R2 overall | | 0.170 | 0.302 | | |
| Instruments | | | | EastTen, DrugDeaths, ChildAb, ChildPov | EastTen, DrugDeaths, ChildAb, ChildPov |

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[a]Hausman test of random vs. fixed effects. Critical $\chi^2$= 0.0186 < 0.05

The main regressions are presented in Table $(4)^{(i)}$. The tobacco use coefficient is the only unexpected sign, but is frequently significant at conventional levels. This contracts the findings of Ariadna Forray (2014) and we believe that tobacco during pregnancy suffers from measurement error due to the fact that the data is relied upon the mother indicating that she used tobacco during pregnancy.

Column (1), (4), and (5) reports that the OLS, 2SLS and LIML coefficients are statistically significant with the low birth weight regression equation [p<0.05]. Under these specifications, controlling for other explanatory variables, a one percent increase in NAS increases the percentage of a low birth weight by about 7.21%-15.61%. Overall, the data fits the model moderately with an R-squared range of 29.20%-30.70%.

Under 2SLS, NAS has a marginally and statistically significant [p< 0.01] large effect on low birth weight than under the OLS, FE, and RE model. Similar results are observed under LIML. However, NAS is slightly larger indicating a 15.61% increase in the probability of a low birth weight rather than 15.32% compared to 2SLS. We suspect these results to be so similar because the data has a relatively small sample, therefore the difference between the two estimation methods is minor.

Neonatal abstinence syndrome (NAS) is an important predictor of low birth weight among babies. Columns (2) and (3) show the differences between fixed effects and random effects estimation, respectively.

We observe that the fixed effects coefficients are not all statistically significant, since only the percent of women who used tobacco during pregnancy ($p<0.05$) is significant. The Hausman test for random and fixed effects suggests to reject random effects in favour of fixed effects [$\chi^2 = 0.0186 < 0.05$] [a], a surprising result given the highly insignificant fixed effects model. Thus, we can assume the variation across counties is random and uncorrelated with the predictor variables. The coefficient on NAS obtained by random effects is similar to OLS, but differed from fixed effects, therefore, we can assume that random effects produces more accurate and precise coefficients relative to fixed effects. The difference of coefficients could be an indication of heteroscedasticity or since fixed effects removes the effect of time-invariant characteristics. We also suspect fixed effects produces insignificant results due to error term correlations.

By contrast, the random effects coefficients are all statistically significant at the 10% level and indicate that when controlling for other explanatory variables, a one percent increase in NAS increases the percentage of a low birth weight by about 5.95%. The R-squared is 30.2%, therefore, this indicates a moderately fit model. The random effect estimation also agrees with the two stage least squares (2SLS), and the limited-information maximum likelihood (LIML) estimators.

Appendix B.2.1. reports the three post estimation tests performed for 2SLS and LIML; endogeneity, first stage, and over identified. For 2SLS and LIML (Table B.2.1.1), the results indicate that the instrumental variables are valid and the endogenous variable in question, NAS, is in fact endogenous. Therefore, after examining our observations, we determine that our endogenous and instrumental variables are valid.

We note that since our panel is extremely short T=4, autocorrelation is not a serious problem and the adjustments [vce(cluster county)] made no significant impact to the model. Therefore, these results were excluded from the model.

**Comparison of Results**

Due to data constraints we were unable to display results based off race. However, it is known that the majority of opioid users in Tennessee are white. In 2015, 90% of deaths from opioid use in Tennessee where white, only 6% were black (Kevin McKenzie USA today, 2015). Our R-squared results are similar to that of Theodore Joyce et al.'s R-squared when comparing our results to the race specific panel of whites (29%-39%). Smoking while pregnant in Theodore Joyce et al.'s results contained a positive coefficient which is what we were anticipating for our model. As mentioned, we believe that the variable for smoking in our model suffers from a high error term which can result in suppression in the variable. We wish to further explore and treat this problem for the final draft. We share similar results to unmarried (wedlock in our model) and continue to believe that stress factors and uncertainties from having a single marital status at the time of birth and pregnancy is reflected on the neonate's health.

The findings of SW Patrick et al.'s (2012) study indicated that NAS babies where likely to have a low birthweight when compared to non-NAS newborns which also aligns with our hypothesis and estimation results. As stated and expressed by our estimation model, teen births correlate with birthweight as a result of lifestyle decisions which we discovered a positive correlation. The findings in Kathryn R Fingar's study shows that maternal stays related to substance use were more likely than other maternal stays to involve young women and to have Medicaid as the expected primary payer. This also raises concern for suppression type effects towards our uninsured variable, similar to that of smoking. Valerie Whiteman et al.'s results also indicated increased odds of threatened preterm labor, early onset delivery and poor fetal growth which is often associated with low birthweight.

Adriana's widely ranged empirical study indicates correlations between smoking and opioid usage and birthweight. While we have similar findings to NAS as an indicator of opioid use during pregnancy and its positive correlation to low birthweight, we have further evidence put forth that there are grounds for investigation for our smoking variable and coefficient.

**Conclusion**

The study further solidifies the existing concern and literature of the effects of neonatal abstinence syndrome on low birth weight. By using multiple estimation methods and four instrumental variables, we have investigated the consequences of neonatal abstinence syndrome in the rate of low birth weight that has occurred in Tennessee over the course of the last 4 years with separate panels across counties from 2013 to 2016. We found that the independent effect of neonatal abstinence syndrome varied throughout estimation methods, but was consistently yielding a 5.95%-15.61% increase in the percentage of a low birth weight. We conclude that the two-stage least squares (2SLS) is the most appropriate model with regards to accounting for endogeneity [R-squared = 29.30%] and resulted in a statistically significant model at the 5% level.

Under 2SLS, our hypothesis is confirmed, therefore, NAS has a positively significant relationship with low birth weight. Thus, we conclude that while keeping all other explanatory variables constant, a one percent increase in NAS increases low birth weight by 15.32%.

Limitations for our study include our access to data for a longer time series and the time frame given to complete this research paper. For ethical reasons and patient confidentiality, the time required to obtain per patient data is lengthy and would take much longer than a semester to receive, compile, and analyze. As mentioned in the introduction, the Tennessee Department of Health only has data available starting from 2013 for NAS reporting and at the time this paper was written, aggregated data for 2017 unfortunately was not processed yet.

## Appendix

Appendix A: Results

Appendix A.1: Instrumental Variable First-Stage Results

Table A.1.1: 2SLS first-stage regressions

First-stage regressions

| | |
|---|---|
| Number of obs | = 380 |
| F( 9, 370) | = 40.98 |
| Prob > F | = 0.0000 |
| R-squared | = 0.5588 |
| Adj R-squared | = 0.5481 |
| Root MSE | = 1.3320 |

| NAS | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TobaccoUseDuringPregancy | .0328579 | .014565 | 2.26 | 0.025 | .0042172 | .0614985 |
| WEDlock | -.0181354 | .0096012 | -1.89 | 0.060 | -.0370151 | .0007444 |
| TeenBirth | -.2183268 | .0970494 | -2.25 | 0.025 | -.4091643 | -.0274893 |
| Uninsured | -.0208738 | .0403598 | -0.52 | 0.605 | -.1002371 | .0584895 |
| TANF | -.063501 | .1513098 | -0.42 | 0.675 | -.361036 | .234034 |
| DummyEastTennessee | 2.371249 | .2143444 | 11.06 | 0.000 | 1.949763 | 2.792735 |
| DrugDeathsIV | .0169052 | .0063212 | 2.67 | 0.008 | .0044752 | .0293352 |
| RepChildAbsCases | .2386547 | .0741044 | 3.22 | 0.001 | .0929361 | .3843732 |
| ChildPov | .0700864 | .0207247 | 3.38 | 0.001 | .0293334 | .1108394 |
| _cons | -.7512514 | .5299579 | -1.42 | 0.157 | -1.793359 | .2908557 |

We note that in Table A.1,1, all the dummy variables are statistically significant at the 1% level and increase the overall fit of the model considerably compared to the second stage regression results. The R-squared of the first stage regressions was 55.88%, compared to 29.30% in the second stage. The LIML first stage regression results in Table B.1.2 are identical to the 2SLS first stage results. The only differences are in the second stage results, where LIML coefficients are, on average, larger.

Table A.1.2: LIML first-stage regressions

First-stage regressions

| | |
|---|---|
| Number of obs | = 380 |
| F( 9, 370) | = 40.98 |
| Prob > F | = 0.0000 |
| R-squared | = 0.5588 |
| Adj R-squared | = 0.5481 |
| Root MSE | = 1.3320 |

| NAS | Coef. | Robust Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| TobaccoUseDuringPregancy | .0328579 | .014565 | 2.26 | 0.025 | .0042172 | .0614985 |
| WEDlock | -.0181354 | .0096012 | -1.89 | 0.060 | -.0370151 | .0007444 |
| TeenBirth | -.2183268 | .0970494 | -2.25 | 0.025 | -.4091643 | -.0274893 |
| Uninsured | -.0208738 | .0403598 | -0.52 | 0.605 | -.1002371 | .0584895 |
| TANF | -.063501 | .1513098 | -0.42 | 0.675 | -.361036 | .234034 |
| DummyEastTennessee | 2.371249 | .2143444 | 11.06 | 0.000 | 1.949763 | 2.792735 |
| DrugDeathsIV | .0169052 | .0063212 | 2.67 | 0.008 | .0044752 | .0293352 |
| RepChildAbsCases | .2386547 | .0741044 | 3.22 | 0.001 | .0929361 | .3843732 |
| ChildPov | .0700864 | .0207247 | 3.38 | 0.001 | .0293334 | .1108394 |
| _cons | -.7512514 | .5299579 | -1.42 | 0.157 | -1.793359 | .2908557 |

# Appendix B: Tests

## B.1. Diagnostic Tests

### Table B.1.1: Diagnostic test summary

| Model | Test | Test Statistic | Rejected or failed | Suggestion |
|---|---|---|---|---|
| FE Model | Time FE test | Prob > F = 0.9478 > 0.05 | Fail to reject | No time FE needed |
| | Pasaran CD Test | Pr = 0.7070 > 0.05 | Fail to reject | No cross-sectional dependence |
| | Modified Wald test for groupwise heteroskedasticity | $X^2$= 0.0000 < 0.05 | Reject | Heteroscedasticity is present |
| | Bias-corrected Born and Breitung (2016) Q(p)-test: Tests for serial correlation up to order p | Lags(1): P = 0.000 < 0.05<br>Lags(2): P = 0.000 < 0.05<br>Lags(3): P = 0.000 < 0.05 | Reject | Some serial correlation up to the 1st, 2nd, and 3rd order |
| | Bias-corrected Born and Breitung (2016) LM(k)-test: Tests for serial correlation of order k | Order (1): P = 0.079 > 0.05<br>Order (2): P = 0.000 > 0.05<br>Order (3): P = 0.000 > 0.05 | Fail to reject | Test indicates data might be free of 1st order serial correlation, not free of 2nd and 3rd order serial correlation |
| | Heteroskedasticity-robust Born and Breitung (2016) HR-test: Tests for first order serial correlation: | P = 0.384 > 0.05 | Fail to reject | Test indicates data might be free of 1st order serial correlation |
| RE Model | Breusch-Pagan Lagrange multiplier (LM) test | $X^2$= 0.0000 < 0.05 | Reject | Random effects regression suggested |
| | Specification tests for linear panel-data models 'xttest1' | RE, Two Sided:<br>1. LM(Var(u)=0) = 56.77<br>Pr>chi2(1) = 0.0000<br>2. ALM(Var(u)=0) = 0.19<br>Pr>chi2(1) = 0.6651<br>RE, One Sided:<br>3. LM(Var(u)=0) = 7.53<br>Pr>N(0,1) = 0.0000<br>4. ALM(Var(u)=0) = -0.43<br>Pr>N(0,1) = 0.6674<br>Serial Correlation:<br>5. LM(lambda=0) = 122.95<br>Pr>chi2(1) = 0.0000<br>6. ALM(lambda=0) = 66.37 Pr>chi2(1) = 0.0000 | 1. Reject<br>2. Fail to reject<br>3. Reject<br>4. Fail to reject<br>5. Reject<br>6. Reject<br>7. Reject | The unadjusted versions of the tests for RE [1 & 3] suggest that random effects is preferred over OLS, assuming no serial correlation.<br>The adjusted versions of the tests for random effects [2&4] suggests that the OLS model is preferred.<br>The unadjusted and adjusted test for serial correlation suggest autocorrelation is present at the 5% level.<br>Results suggest that the possible misspecification is more likely due to the presence serial correlation than random effects. Thus, the change in preferred models is due to the presence of serial correlation in both versions. |
| | CD-test for cross-sectional dependence | Pr = 0.1894 > 0.05 | Fail to reject | No cross-sectional dependence |

| | | | | |
|---|---|---|---|---|
| | Over identifying restrictions test | P = 0.0020 < 0.05 | Reject | This test confirms the Hausman test that the FE model seems to be more appropriate to estimate our model. |
| OLS Model | Breusch-Pagan / Cook-Weisberg test for heteroskedasticity | $X^2$= 0.3301 > 0.05 | Fail to reject | Heteroscedasticity is not present (variances are homoscedastic) |
| Other Tests | Serial Correlation for panel model | Prob > = 0.0111 < 0.05 | Reject | First-order autocorrelation is present |
| | Hausman Test | $X^2$= 0.0186 < 0.05 | Reject | Prefer fixed effects |

B.2. Instrumental Variable Post Estimation Tests: 2SLS & LIML

B.2.1. 2SLS Post Estimation Tests

Since we suspect that neonatal abstinence syndrome (NAS) is an endogenous variable, we must perform IV methods to provide a way to nonetheless obtain consistent parameter estimates. Once these tests are conducted we execute three post-estimation tools to detect any weak instruments and to confirm NAS as endogenous; estat endogenous, estat firststage, and estat overid.

*estat endogenous* implements tests to detect whether endogenous regressors in the model are in fact exogenous. If the test statistic is significant, then the variables being tested must be treated as endogenous. estat endogenous is not available after LIML estimation. The last line of output is the robustified DWH test and leads to strong rejection of the null hypothesis that NAS is exogenous. We conclude that NAS is endogenous. For the two stage least squares test (2SLS) we observed that since p = 0.0094< 0.05, we reject the null hypothesis at the 5% significance level and conclude that NAS is endogenous.

*estat firststage* indicates various statistics that measure the importance of the excluded exogenous variables. By default, whether the equation has one or more than one endogenous regressor determines what statistics are reported. For the 2SLS test, since the F-statistic = 0 > 10, the instrument variables are not weak.

*estat overid* performs tests of overidentifying restrictions. Sargan's (1958) and Basmann's (1960) $\chi$ 2 tests as well as Wooldridge's (1995) robust score test, are reported since the 2SLS estimator was used. However, since we also used the LIML estimator, Anderson and Rubin's (1950) $\chi$ 2 test and Basmann's F test are reported. A statistically significant test statistic always indicates that the instruments may not be valid. Since we have an overidentified model, we have more instruments than we need. In the first stage test, we determined that our chosen instrument variable is not weak, therefore the instrument is valid. Since this is the case, under the assumption that at least one of the instruments are valid, we can test the validity of the others (the "overidentifying" restrictions). For the 2SLS test, since p = 0.9711 > 0.05, we conclude that the test statistics are not significant at the 5% level, which means that either one or more of our instruments are valid.

Table B.2.1.1: Post estimation tests for instrumental variable regression

| Model | Test | Test Statistic | Rejected or Failed | Suggestion |
|---|---|---|---|---|
| 2SLS | Endogeneity test - DWH test | P = 0.0116 < 0.05 | Reject | NAS is endogenous |
| | Report first-stage stats | F = 54.9889 > 10 | We firmly reject the null hypothesis | Instruments are not weak |
| | Overidentifying test | Score chi2(3) = 6.7752, p = 0.0794 > 0.05 | Fail to reject | One or more of the instruments are valid |
| LIML | Endogenous test | Not applicable in LIML estimator | | |
| | Report first-stage stats | F = 54.9889 > 10 | We firmly reject the null hypothesis | Instruments are not weak |
| | Overidentifying test | Basmann F(3,370) = 2.131, p = 0.0959 > 0.05 | Fail to reject | One or more of the instruments are valid |

## B.2.2. Further Weak Instrument Tests

Table B.2.2.1: Endogenous variable regressed on instrument variables

```
. regress NAS DrugDeathsIV DummyEastTennessee RepChildAbsCases ChildPov
```

| Source | SS | df | MS | Number of obs | = | 380 |
|---|---|---|---|---|---|---|
| | | | | F(4, 375) | = | 105.42 |
| Model | 787.648519 | 4 | 196.91213 | Prob > F | = | 0.0000 |
| Residual | 700.425797 | 375 | 1.86780213 | R-squared | = | 0.5293 |
| | | | | Adj R-squared | = | 0.5243 |
| Total | 1488.07432 | 379 | 3.92631746 | Root MSE | = | 1.3667 |

| NAS | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| DrugDeathsIV | .0214952 | .005582 | 3.85 | 0.000 | .0105192 | .0324712 |
| DummyEastTennessee | 2.435728 | .17024 | 14.31 | 0.000 | 2.100984 | 2.770473 |
| RepChildAbsCases | .2849884 | .0633959 | 4.50 | 0.000 | .1603324 | .4096444 |
| ChildPov | .043635 | .0124039 | 3.52 | 0.000 | .0192449 | .068025 |
| _cons | -2.002044 | .3535892 | -5.66 | 0.000 | -2.69731 | -1.306778 |

Table B.2.2.1 indicates a moderate/strong correlation between the endogenous variable NAS and the instrument variables. Therefore, we believe these instrument variables to be strong instruments and good predictors of NAS.

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