HIDI HealthStats

Statistics and Analysis From the Hospital Industry Data Institute

JANUARY 2019 ■ Predicting Opioid Risk In Hospital Patients

The Opioid Crisis in Missouri

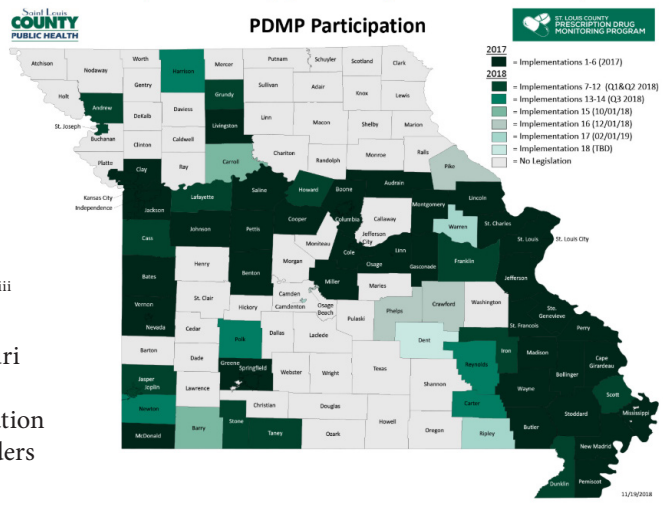
- The **opioid-related mortality rate** in Missouri **increased by 732 percent** between 1999 and 2016.[iv]
- The total **economic cost** of the opioid epidemic in Missouri was estimated at **$12.6 billion, or 4.2 percent of GDP,** in 2016.[v]
- The incidence of newborns diagnosed with **neonatal abstinence syndrome increased 353 percent** in Missouri between 2008 and 2016.[vi]
- The rate of **hospital utilization** for prescription opioid misuse in Missouri **increased 138 percent** between 2006 and 2015[vii] and 16 percent between 2016 and 2017.

HIDI
HOSPITAL INDUSTRY DATA INSTITUTE
The Data Company of the Missouri Hospital Association

Background

Risk identification tools are critical to clinicians and prescribers working to reverse the societal damage caused by the ongoing opioid crisis. For the third consecutive year, life expectancy decreased in the U.S. during 2017, largely because of the ongoing opioid epidemic. And yet again, the rate of drug overdose deaths in Missouri was higher than the national average, according to the Centers for Disease Control and Prevention.[i]

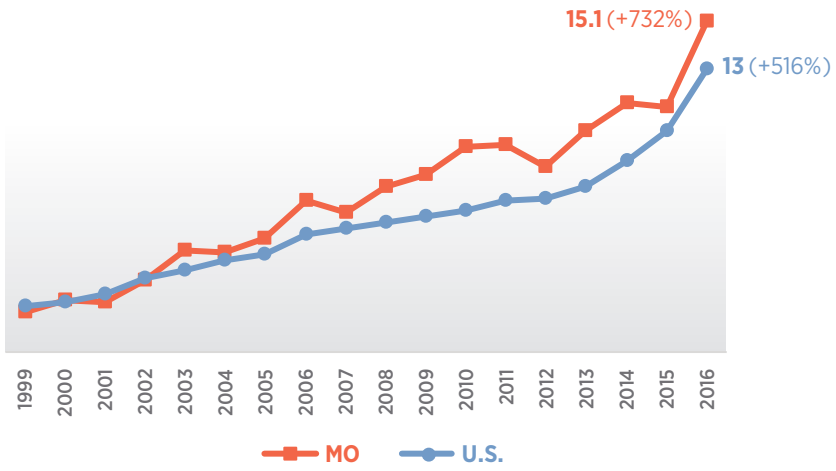
As the only state in the country without a state-legislated prescription drug monitoring program, health care providers in Missouri historically have faced a profound disadvantage in identifying and treating patients with, or at risk of, developing opioid use disorder. Recent research discovered that robust use of statewide PDMPs have the capacity to greatly reduce the supply of opioids, with an annual reduction of 24 to 308 milligrams prescribed per capita.[ii] Robust PDMPs are defined as having universal prescriber access, a comprehensive and frequent use mandate, weekly or more frequent data refreshes, monitoring of all schedule II-IV controlled substances, mandatory registration, provider access by proxy, proactive reporting, no immunity for failure to query the system, and being operated by a health agency.[ii]



CDC describes integrated and routine use of PDMPs into clinical care as "among the most promising state-level interventions to improve opioid prescribing, inform clinical practice and protect patients at risk."[iii] Coverage through a robust PDMP in Missouri now covers more than 80 percent of the population and 90 percent of providers thanks to leadership of the St. Louis County Department of Public Health's PDMP system. However, there still are more than 50, primarily rural, counties and municipalities outside of the PDMP network. Data continue to suggest that Missouri is disproportionately impacted by the opioid epidemic:

- According to CDC data, the opioid-related mortality rate in Missouri increased by 732 percent between 1999 and 2016 (Figure 1).[iv]
- The total **economic cost** of the opioid epidemic in Missouri was estimated at **$12.6 billion, or 4.2 percent of GDP,** in 2016.[v]
- The incidence of newborns diagnosed with **neonatal abstinence syndrome,** or withdrawal from maternal exposure to drug use, **increased 353 percent** in Missouri between 2008 and 2016.[vi]
- The rate of **hospital utilization** for prescription opioid misuse in Missouri **increased 138 percent** between 2006 and 2015 (using ICD-9 data)[vii] and 16 percent between 2016 and 2017 (using ICD-10 data).
- Individuals with OUD are at risk of experiencing multiple social and biological adverse outcomes as a result of their dependence. In addition to premature death associated with opioid overdose, individuals with OUD are more likely to experience unplanned hospitalization and emergency department encounters, episodic mental health disorders including suicide and self-harm, polysubstance use, onset of clinical comorbidities and infections, encounters with law enforcement, and difficulties acquiring and maintaining gainful employment.[viii, ix, x]

Figure 1: Opioid Overdose Death Rates per 100,000



Source: Centers for Disease Control and Prevention

To assist health care providers with identifying patients at risk of experiencing an unplanned hospitalization or ED visit for OUD, a predictive model was developed using hospital discharge records, occurring between Oct. 1, 2015, and June 30, 2018, for 2.6 million Missouri adults. In addition to information gathered from the St. Louis County PDMP, risk prediction modeling can be used to improve the likelihood of reducing adverse outcomes attributable to OUD in Missouri. The model results are scheduled to be available to clinicians and prescribers in near real-time through HIDI Advantage® Alerts and Notifications.

HIDI Advantage® Alerts and Notifications

To enable near real-time event notification, HIDI developed encounter notifications and alerting solution-based messaging among connected hospitals within its HIDI Advantage platform. The transmission of ADT messages triggers notification for patients identified on watchlists. There are two primary types of watchlists within the HIDI Advantage platform – Care Coordination Notifications and Context Enhanced Notifications. With CCNs, participating hospitals define a cohort of patients for whom it wishes to receive alerts based on encounters with other participating hospitals. With CENs, HIDI creates the patient cohort based on proprietary analytic models, such as the opioid risk model. When a high-risk patient in this cohort presents at a hospital, an alert is issued in near real-time.

With both types of watchlists, there are four events that may trigger an alert about a patient on a watchlist.

1. inpatient admission
2. emergency department registration
3. transfer from outpatient to inpatient status
4. discharge

Once an alert is triggered, an email is sent to designated individuals at the participating hospital. This email includes basic information that a notification exists and that they should log in to the HIDI Advantage Alert portal to view the notification. When viewing the notification screens, hospital staff are able to view a list of notifications received, as well as drill into a patient-specific view to see all alerts related to that individual.

Predictive Model Specification

To demonstrate the value of using hospital discharge data to predict patients at risk of opioid-related hospital utilization, a retrospective study was conducted of Missouri adults with an ED encounter or inpatient hospitalization occurring between October 2015 and June 2018. The study cohort included all payers ages 18 and older, resulting in a sample of 2,607,625 unique patients. Opioid-related hospital encounters were detected using arrays of diagnosis codes present at any position on the patient's discharge record (F11.xxx, R781, T401.xxx-T404.xxx and Z79891). A total of 103,940 patients, or 4 percent of the full sample, were identified as having one or more opioid-related hospital encounters during the study period. Patients meeting this criteria (described as the OUD cohort for descriptive purposes) served as the dependent variable in model development.

There were 29 predictors (independent variables) selected through literature review[xi, xii, xiii, xiv] for use in the model. These explanatory variables were categorized into four risk domains: sociodemographic factors, OUD risk factors, behavioral risk factors and clinical risk factors. The OUD cohort exhibited significantly higher rates of all risk characteristics used as predictors in the model (Table 1). Compared to the entire sample, this included 12 times the rate of diagnosis for malingering (feigning illness or pain), four times the rate of diagnosis for social determinants, triple the rate of traumatic injury, and more than twice as many diagnosed with lumbago or other pain-related conditions during the study period.

A logistic regression model was fit to the data to estimate the risk each patient had of experiencing an opioid-related hospital encounter during the study period using information on the 2.6 million patients' sociodemographic status, OUD risk, behavioral risk and presence of clinical comorbidities that were identified in 7,788,971 inpatient and ED visits with discharge occurring during the study period.

> Forty-three percent of patients who die of a heroin overdose in a Missouri hospital experienced a prescription opioid–related hospital encounter during the previous four years.[xv]

To test for internal validity, the full sample was partitioned into two randomly selected, equal-sized cohorts, each consisting of 1.3 million unique patients. The two random samples were used to test for differences in model performance between the full cohort model, and the randomly selected development and validation cohort models. Table 1 includes summary statistics for the full, development and validation model cohorts. No statistically significant differences were observed in the frequencies of model predictors observed between the three cohorts.

Results for the development, validation and full models are included in Table 2. With the exception of gender across each model and African American race in the validation model, the coefficients for each of the included explanatory variables were statistically significant in all three models ($P \leq 0.0003$). Estimated coefficients also were similar in size and direction. The strongest predictor of opioid-related hospital utilization was nonopioid substance use disorders (OR = 5.36-5.62, $P<0.0001$), followed by lumbago (OR = 2.07-2.08, $P<0.0001$) and traumatic injury-related diagnoses (OR = 1.87-2.14, $P<0.0001$). Each model featured strong ability to accurately discriminate which patients would experience an opioid-related hospital encounter during the study period (C-statistic = 0.83).

To test for external validity and evaluate the predictive ability of the model, the coefficients generated with the development model were applied to patients in the validation model cohort. The probability each randomly selected validation model patient had of having an opioid-related hospital encounter during the study period was calculated with a logarithmic transformation of the development model coefficients applied to the characteristics of randomly selected patients in the validation model cohort. The results were grouped into predicted probabilities rounded to the nearest integer between one and 100 and compared to the observed percentage of those patients who actually experienced an opioid-related hospital encounter. Univariate analysis suggests that the predicted probability of experiencing an opioid-related hospital encounter derived with the development model coefficients explained 97 percent of the variation in the actual probability of an opioid-related hospital encounter in the fully independent validation model patient cohort (Figure 2). In addition, applying the development model coefficients to the validation model cohort isolated 70 percent of patients who actually experienced an opioid-related hospital encounter during the study period into 20 percent of patients with the highest predicted risk of experiencing the same event (Figure 3).

Table 1: Variable Frequency for OUD Predictive Model Development, Validation and Full Cohorts: Missouri Residents Ages 18+ Inpatient and ED Discharges, October 2015 – June 2018

	Parameter	Develop-ment Model	Validation Model	Full Model	OUD Cohort	
					Frequency	Percent Difference
	Sample Size	1,303,813	1,303,812	2,607,625	103,940	-
	OUD Cohort w/hospital utilization for opioid misuse	4.0%	4.0%	4.0%	100.0%	-
Sociodemographic Factors	Age (mean)	48.81	48.81	48.81	52.32	7.2%
	Male	43.8%	43.8%	43.8%	45.7%	4.4%
	Race white	79.7%	79.7%	79.7%	83.8%	5.2%
	Race African American or black	15.6%	15.6%	15.6%	14.7%	-5.4%
	Social determinant of health diagnosis	5.1%	5.1%	5.1%	22.1%	335.9%
	Medicaid primary payer	12.7%	12.7%	12.7%	24.8%	95.0%
	Uninsured-self-pay/charity primary payer	20.9%	20.9%	20.9%	27.2%	29.9%
	Number of residential census tracts (mean)	1.21	1.21	1.21	1.62	34.4%
	High deprivation census tract-ADI q5	17.1%	17.1%	17.1%	20.6%	20.6%
OUD Risk Factors	Number of hospital IP & ED visits (mean)	2.99	2.98	2.99	8.61	188.3%
	Number of hospitals visited (mean)	1.43	1.43	1.43	2.35	63.9%
	Pain-related diagnosis	32.7%	32.7%	32.7%	65.5%	100.6%
	Lumbago-related diagnosis	15.4%	15.4%	15.4%	43.7%	183.3%
	Traumatic injury-related diagnosis	0.2%	0.3%	0.2%	0.8%	215.3%
	Malingering diagnosis-feigning illness	0.2%	0.2%	0.2%	3.0%	1108.9%
Behavioral Risk Factors	Psychological disorder	6.0%	6.0%	6.0%	20.2%	237.7%
	Alcohol use disorder	4.8%	4.8%	4.8%	14.1%	195.8%
	Substance use disorder	2.5%	2.5%	2.5%	15.3%	523.1%
	Smoker	41.8%	41.6%	41.7%	73.0%	75.0%
	Obese	10.2%	10.2%	10.2%	22.6%	122.1%
Clinical Risk Factors	COPD diagnosis	10.8%	10.8%	10.8%	28.3%	162.5%
	Stroke diagnosis	4.2%	4.2%	4.2%	9.2%	119.4%
	Diabetes diagnosis	15.9%	15.9%	15.9%	29.9%	87.7%
	Hypertension diagnosis	35.7%	35.6%	35.7%	58.3%	63.3%
	Heart disease diagnosis	29.8%	29.8%	29.8%	54.6%	83.1%
	Liver disease diagnosis	6.1%	6.1%	6.1%	17.7%	190.3%
	Asthma diagnosis	8.1%	8.1%	8.1%	16.8%	106.5%
	Cancer diagnosis	8.1%	8.1%	8.1%	17.7%	118.8%
	Atherosclerosis diagnosis	11.7%	11.7%	11.7%	25.4%	116.7%

Table 2: Parameter Estimates for OUD Predictive Model Development, Validation and Full Cohorts: Missouri Residents Ages 18+ Inpatient and ED Discharges, October 2015 – June 2018

		Development Model			Validation Model			Full Model		
Parameter		Estimate	P-Value	Odds Ratio	Estimate	P-Value	Odds Ratio	Estimate	P-Value	Odds Ratio
Intercept		-5.52	<.0001		-5.41	<.0001		-5.46	<.0001	
Sociodemographic Factors	Age (mean)	0.00	<.0001	1.00	0.00	<.0001	1.00	0.00	<.0001	1.00
	Male	-0.01	0.595	1.00	-0.01	0.504	0.99	-0.01	0.396	0.99
	Race white	0.50	<.0001	1.65	0.41	<.0001	1.51	0.46	<.0001	1.58
	Race African American or black	0.17	<.0001	1.18	0.04	0.203	1.05	0.11	<.0001	1.11
	Social determinant of health diagnosis	0.40	<.0001	1.50	0.40	<.0001	1.49	0.40	<.0001	1.50
	Medicaid primary payer	0.18	<.0001	1.20	0.20	<.0001	1.22	0.19	<.0001	1.21
	Uninsured-self-pay/charity primary payer	0.07	<.0001	1.07	0.05	<.0001	1.05	0.06	<.0001	1.06
	Number of residential census tracts (mean)	-0.06	<.0001	0.94	-0.06	<.0001	0.94	-0.06	<.0001	0.94
	High deprivation census tract-ADI q5	0.09	<.0001	1.09	0.09	<.0001	1.09	0.09	<.0001	1.09
OUD Risk Factors	Number of hospital IP & ED visits (mean)	0.02	<.0001	1.02	0.02	<.0001	1.02	0.02	<.0001	1.02
	Number of hospitals visited (mean)	0.18	<.0001	1.20	0.17	<.0001	1.19	0.18	<.0001	1.19
	Pain-related diagnosis	0.63	<.0001	1.88	0.62	<.0001	1.87	0.63	<.0001	1.87
	Lumbago-related diagnosis	0.73	<.0001	2.08	0.73	<.0001	2.07	0.73	<.0001	2.07
	Traumatic injury-related diagnosis	0.63	<.0001	1.87	0.76	<.0001	2.14	0.70	<.0001	2.00
	Malingering diagnosis-feigning illness	0.48	<.0001	1.62	0.55	<.0001	1.73	0.52	<.0001	1.68
Behavioral Risk Factors	Psychological disorder	0.37	<.0001	1.45	0.38	<.0001	1.47	0.37	<.0001	1.46
	Alcohol use disorder	-0.31	<.0001	0.73	-0.33	<.0001	0.72	-0.32	<.0001	0.73
	Substance use disorder	1.68	<.0001	5.36	1.73	<.0001	5.62	1.70	<.0001	5.49
	Smoker	0.67	<.0001	1.96	0.64	<.0001	1.91	0.66	<.0001	1.93
	Obese	0.17	<.0001	1.18	0.17	<.0001	1.19	0.17	<.0001	1.18
Clinical Risk Factors	COPD diagnosis	0.25	<.0001	1.28	0.23	<.0001	1.25	0.24	<.0001	1.27
	Stroke diagnosis	0.09	<.0001	1.10	0.12	<.0001	1.12	0.10	<.0001	1.11
	Diabetes diagnosis	0.16	<.0001	1.17	0.14	<.0001	1.15	0.15	<.0001	1.16
	Hypertension diagnosis	0.26	<.0001	1.30	0.30	<.0001	1.35	0.28	<.0001	1.32
	Heart disease diagnosis	0.04	0.000	1.05	0.06	<.0001	1.06	0.05	<.0001	1.05
	Liver disease diagnosis	0.36	<.0001	1.43	0.38	<.0001	1.46	0.37	<.0001	1.45
	Asthma diagnosis	0.09	<.0001	1.09	0.12	<.0001	1.13	0.10	<.0001	1.11
	Cancer diagnosis	0.49	<.0001	1.63	0.46	<.0001	1.58	0.47	<.0001	1.61
	Atherosclerosis diagnosis	0.13	<.0001	1.14	0.11	<.0001	1.12	0.12	<.0001	1.13
Observations		**1,303,813**			**1,303,812**			**2,607,625**		
OUD Cohort (dependent variable)		**3.98%**			**3.99%**			**3.99%**		
C-Statistic		**0.830**			**0.829**			**0.829**		

Figure 2: Validation Model Predicted vs. Observed Rates of OUD Derived With Development Model Coefficients

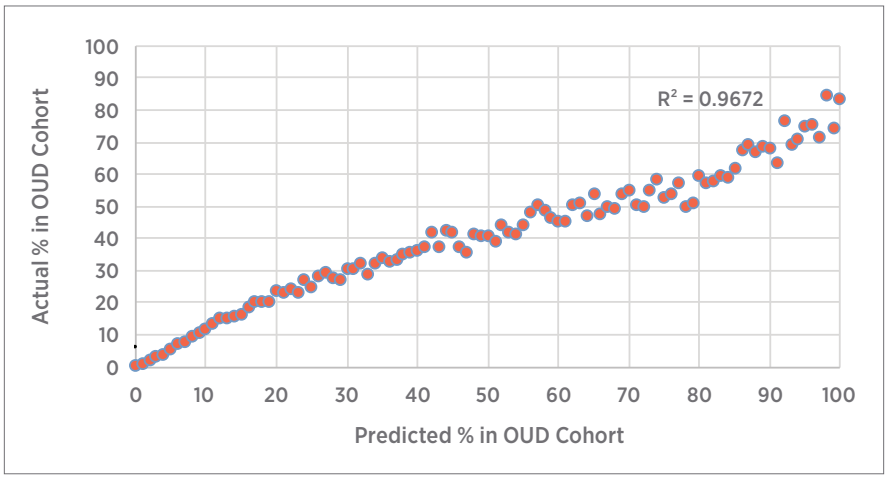
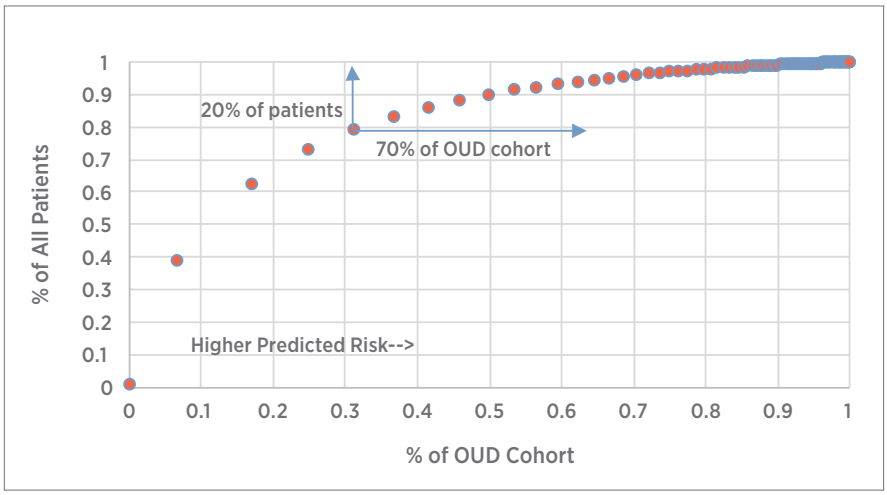


Figure 3: Validation Model Derived with Development Model Coefficients Inequality Line for All Patients vs. OUD Cohort by Predicted OUD Risk Percentiles



Missouri continues to be disproportionately impacted by the opioid epidemic. The ongoing toll may be an artifact of its distinction as the only state without a state-legislated PDMP.

Conclusion

These results suggest the model has a strong ability to prospectively identify patients who will experience an opioid-related hospital encounter. Delivering this risk information to the point of care could provide powerful information to help providers improve outcomes for Missourians with, or at risk of, developing OUD. This includes reducing the rapidly growing rate of opioid-related overdose deaths in the state — 43 percent of patients who die of a heroin overdose in a Missouri hospital experienced a prescription opioid–related hospital encounter during the previous four years.[xv]

Recent data from state and national sources suggest Missouri continues to be disproportionately impacted by the opioid epidemic. Despite significant advances in the availability of an evidence-based PDMP system in areas of the state and other successful interventions, the ongoing toll of the epidemic in Missouri may be an artifact of its distinction as the only state without a state-legislated PDMP. This places Missouri's clinicians and prescribers in a position of "catch-up" with regard to reversing the nearly two-decade trend of overdose deaths and other adverse outcomes related to OUD in the state.

Large geographic areas remain in Missouri, where health care providers are limited to their own experiences and observational data to identify patients with, or at risk of, developing OUD. Availability of the model results provided in near real-time to the point of care would greatly enhance clinician and prescribers' ability to identify high-risk patients and moderate the impact of the opioid crisis in Missouri.

Suggested Citation

Reidhead, M. (2019, January). Predicting Opioid Risk In Hospital Patients. *HIDI HealthStats.* Missouri Hospital Association. Hospital Industry Data Institute. Available at *http://web.mhanet.com/hidi-analytics-research*

[i] Lopez, G. (2018, November 29). Drug overdose deaths were so bad in 2017, they reduced overall life expectancy. Vox. Retrieved from https://www.vox.com/science-and-health/2018/11/29/18117906/opioid-epidemic-drug-overdose-deaths-2017-life-expectancy

[ii] Haffajee, R. L., Mello, M. M., Zhang, F., Zaslavsky, A. M., Larochelle, M. R. & Wharam, J. F. (2018). Four states with robust prescription drug monitoring programs reduced opioid dosages. *Health Affairs, 37*(6), 964-974. Retrieved from https://www.healthaffairs.org/doi/10.1377/hlthaff.2017.1321

[iii] Centers for Disease Control and Prevention. (2017, October 3). What States Need to Know About PDMPs. Retrieved from https://www.cdc.gov/drugoverdose/pdmp/states.html

[iv] Centers for Disease Control and Prevention, National Center for Health Statistics. Multiple Cause of Death 1999-2016 on CDC WONDER Online Database, released December, 2017. Data are from the Multiple Cause of Death Files, 1999-2016, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. Retrieved from http://wonder.cdc.gov/mcd-icd10.html

Note: Opioid-related deaths were identified with ICD-10 Codes T40.0 (Opium), T40.1 (Heroin), T40.2 (Other opioids), T40.3 (Methadone) and T40.4 (Other synthetic narcotics).

[v] Reidhead, M. (2018, February). The Economic Cost of the Opioid Epidemic in Missouri. *HIDI HealthStats.* Missouri Hospital Association. Hospital Industry Data Institute. Available at http://bit.ly/HIDIHealthStats0118

[vi] Reidhead, M., Kinkade, B. & Williams, A. (2018, June). An Ounce of Prevention for Mothers and Newborns: Reducing In-Utero Opioid Exposure in Missouri. *Policy Brief.* Missouri Hospital Association. Available at http://bit.ly/PB_NAS

[vii] Reidhead, M. (2017). Trends in Hospital Utilization for Opioid Overuse and Drug-Dependent Newborns in Missouri. Presentation. Missouri Hospital Association. Available at https://web.mhanet.com/SQI/opioid/NAS_Research.pdf

[viii] Sanger, N., Bhatt, M., Zielinski, L., et al. (2018). Treatment outcomes in patients with opioid use disorder initiated by prescription: A systematic review protocol. *Systematic Reviews, 7*(1), 16. doi: 10.1186/s13643-018-0682-0.

[ix] Larney, S., Hickman, M., Fiellin, D. A., et al. (2018). Using routinely collected data to understand and predict adverse outcomes in opioid agonist treatment: Protocol for the Opioid Agonist Treatment Safety (OATS) Study. *BMJ Open, 8*(8), e025204. doi: 10.1136/bmjopen-2018-025204.

[x] Krueger, A. B. (2016, October 4). Where have all the workers gone? *Paper Prepared for the Boston Federal Reserve Bank's 60th Economic Conference.* Available at https://drive.google.com/file/d/0B7m8wQD_ckP4VmZPOXpza3h4X0E/preview

[xi] Substance Abuse and Mental Health Services Administration, Center for the Application of Prevention Technologies. (2016, May). CAPT Decision-Support Tools. P*reventing Prescription Drug Misuse: Understanding who is at Risk.* (Pub.). Retrieved from https://www.samhsa.gov/capt/sites/default/files/resources/preventing-prescription-drug-misuse-understanding.pdf

[xii] Dilokthornsakul, P., Moore, G., Campbell, J. D., Lodge, R., Traugott, C., Zerzan, J., Allen, R. & Page, R. L. (2016). Risk factors of prescription opioid overdose among Colorado Medicaid beneficiaries. *Journal of Pain, 17*(4), 436-443. Retrieved from https://www.jpain.org/article/S1526-5900(15)00985-2/pdf

[xiii] Hylan, T. R., Von Korff, M., Saunders, K., Masters, E., Palmer, R. E., Carrell, D., Cronkite, D., Mardekian, J. & Gross, D. (2015). Automated prediction of risk for problem opioid use in a primary care setting. *Journal of Pain, 16*(4), 380-387. Retrieved from https://www.jpain.org/article/S1526-5900(15)00049-8/pdf

[xiv] Cochran, B. N., Flentje, A., Heck, N. C., et al. (2014). Factors predicting development of opioid use disorders among individuals who receive an initial opioid prescription: Mathematical modeling using a database of commercially-insured individuals. *Drug and Alcohol Dependence, 138,* 202-208. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4046908/

[xv] Reidhead, M. (2017, May). Drug deaths increase among middle-aged, white Missourians. *HIDI HealthStats.* Missouri Hospital Association. Hospital Industry Data Institute. Available at http://bit.ly/May2017HealthStats

HOSPITAL INDUSTRY DATA INSTITUTE
The Data Company of the Missouri Hospital Association

P.O. Box 60
Jefferson City, MO 65102-0060