Identifying industry and time trends in lead exposure in OSHA laboratory measurements using semi-continuous models to account for possible true zeros in left-censored data

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Missing exposure concentration data

- Common problem
- Concentration below method detection limit (<LOD)
  - Range from 0 to >90% of data
- Multiple solutions
  - Logistic regression (e.g. ≥ Threshold vs. < Threshold)
  - ß-Substitution
  - Maximum likelihood
  - Imputation (e.g., using PROC LIFEREG, Lubin et al. 2004)
  - Tobit models
  - Bayesian approaches

Assumptions:

- **Exposure is present but not quantified**
- **Single exposure distribution**

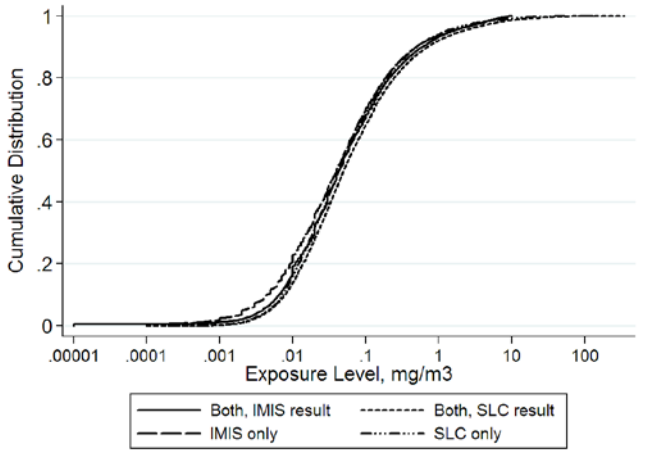
Analyte panels: Mixed distribution? True ‘zeros’?

- Measurement focus on X agent, but…
  - Multiple agents quantified and reported by lab
  - Primary agent(s) not identified in lab data set
  - E.g., metal panels

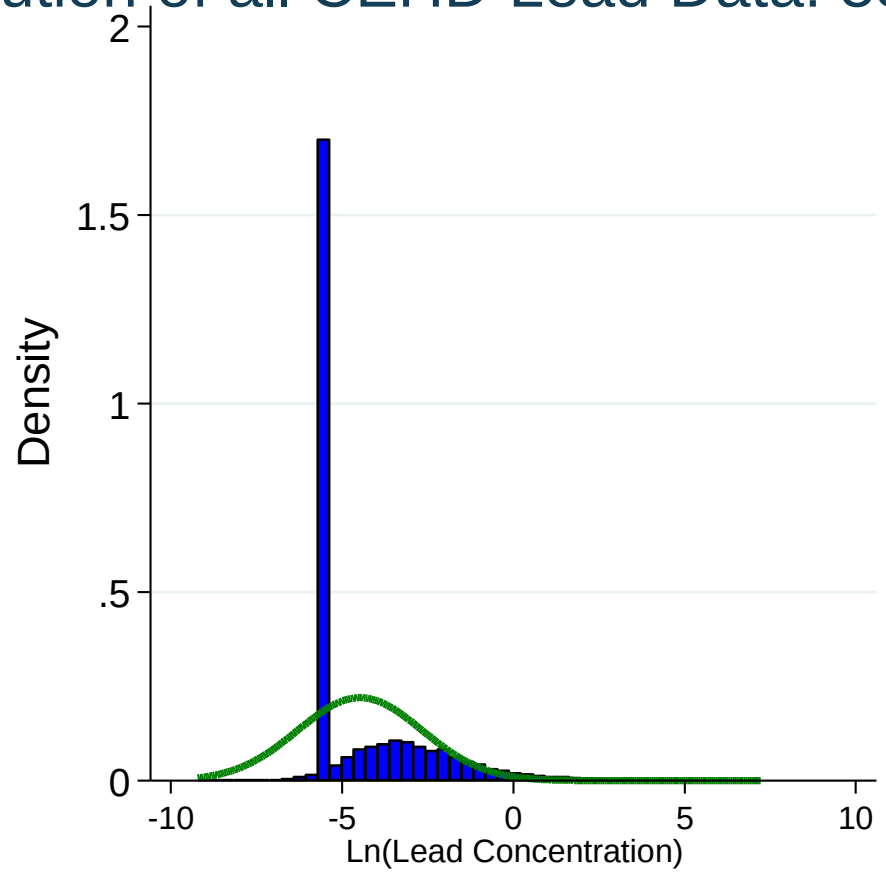
Case Study: Varying % LOD by data source

- OSHA inspection lead measurements (Lavoue et al. 2013)
  - Laboratory msmts: Chemical Exposure Hazard Database (CEHD) from Salt Lake City Laboratory
  - Inspection results: Integrated Management Information System (IMIS)

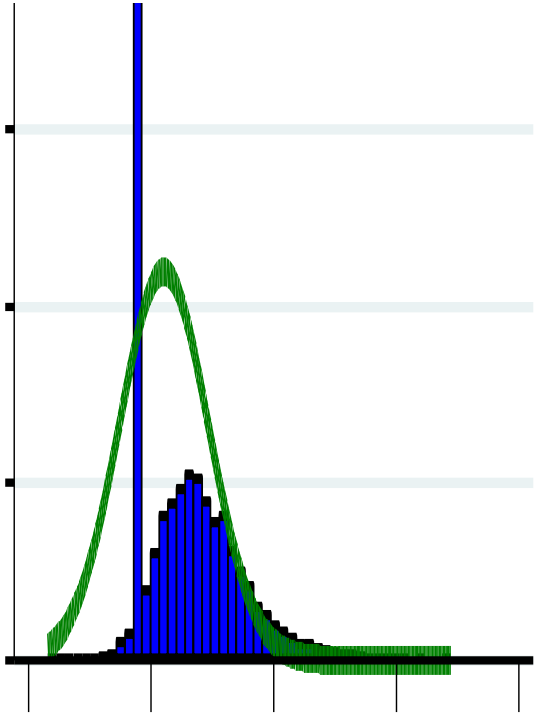
	% Sample	% < LOD
Both IMIS-CEHD	50	50
IMIS only	23	46
CEHD only	27	74



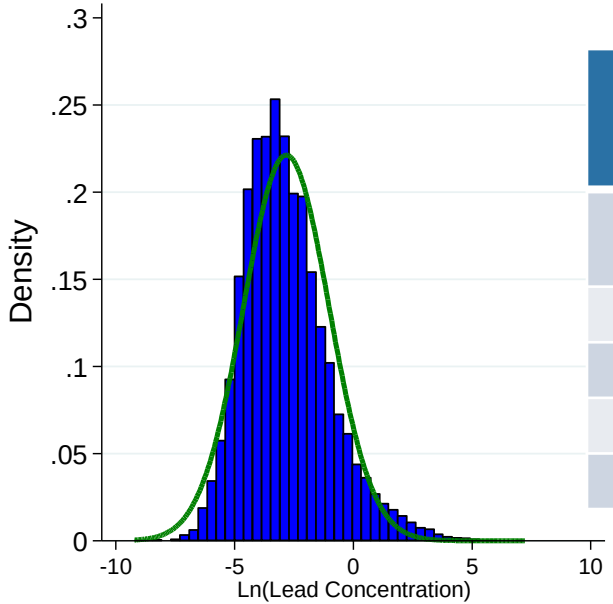
Distribution of all CEHD Lead Data: 58% not detected



CEHD Data



Assuming all ND's are absent



% True Zeros	GM (mg/m3)	Relative difference
0	0.011	**Ref.**
25	0.014	**1.3**
50	0.018	**1.6**
75	0.028	**2.5**
100	0.059	**5.4**

Can’t disentangle ‘present but not quantified’ vs. ‘true zero’

- Assume ‘present’ ?
  - E.g., imputation, MLE, substitution
  - Underestimate true exposure scenarios
  - Overestimate ‘true zero’ or ‘absent’ scenarios
- Restrict data set or two stage model ?
  - A priori knowledge about presence of exposure?
  - Base on likelihood of detection?
  - Ignores covariance, biased estimates
  - Narrows generalizability and inference

Semi-continuous modeling: CEHD lead data

- Joint modeling:
  1) Logistic regression:
     - Probability of detecting lead ≥7 μg/m^3.
  2) Linear regression:
     - Predictors of concentrations ≥7 μg/m^3

  - Set threshold at highest LOD over time period/method
  - Includes co-variance term for two model components
  - Allows one random-effect term per model (4-digit SIC code)
  - Allows different predictors for each model component

Descriptive evaluation

- 52,457 measurements
- 62% <0.007 mg/m^3
  - 75% ICP, 34% AAS
- 575 SIC4
  - Median 14 measurements (IQR 3-61)
  - Median 11% measurements ≥0.007 mg/m^3 (IQR 0-35%)
  - 203 SIC4 codes with no measurements ≥0.007 mg/m^3
  - N measurements does not predict % detected (rho = 0.44)

Determinants of exposure

	Probability ≥7 µg/m^3	Concentration
Year	↘ with time	≠
Analytical Method	ICP << AAS	ICP < AAS
Panel sample	No < Yes*	Yes < No
Sample duration	0-60 < 60-120 < 120-600	0-60 > 60-120 > 120-600
OSHA plan	State/Partial < Federal	State/Federal < Partial
Broad SIC grp (1-digit SIC)	RRs: 0.86-4.6	RRs: 1.0-2.4
Year-interactions	Yes	Yes

*Correlated with analytical method. All ICP samples were panel samples.

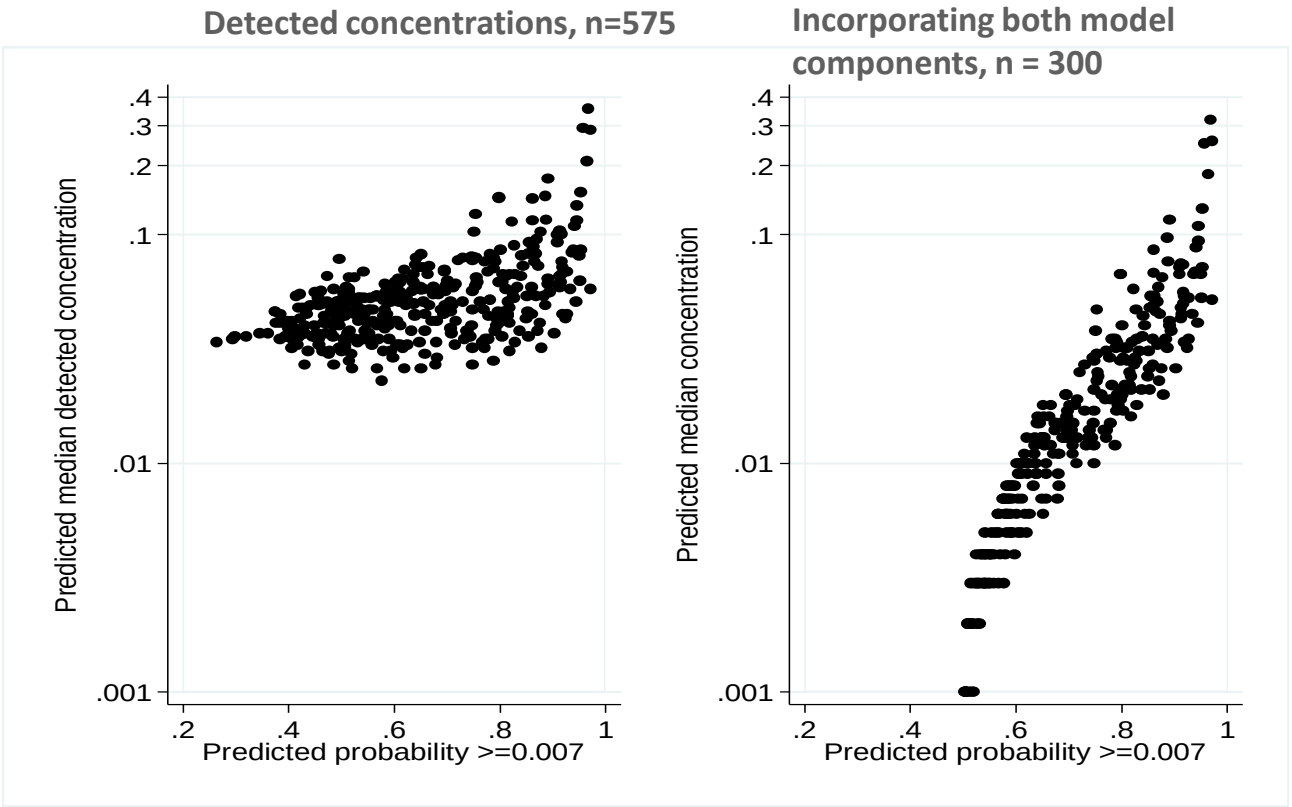
Obtaining SIC-specific estimate of exposure

- If SIC4 probability ≥0.007 mg/m^3 is <50%, then **SIC4 GM <0.007 mg/m^3**

- If SIC4 probability ≥0.007 mg/m^3 is ≥50%, then used distributional parameters from the cumulative distribution function to estimate exposure
  - 95% confidence intervals by bootstrap

For example, if the probability was 30% from the logistic component, we would obtain the ~20th percentile from linear regression component

Predicted SIC4 Pb concentration in mg/m^3, by predicted probability



Summary

Non-trivial covariance between models → joint modeling necessary

Strengths

- Inclusion of all data increases population-level generalizability
- Flexible modeling framework
- No assumptions on whether censored data were true zeros or present but unquantified

Limitations

- Limited to single threshold value,
- 1 random effect per component
- Some complexity in prediction using both components → code available

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