Online Supplementary Materials for

Toxic Neighborhoods: The Effects of Concentrated Poverty and Environmental Lead Contamination on Early Childhood Development

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Part A: Exposure-mediator Interaction

In this section, we report estimates of the controlled direct and mediator effects from models that allow for interaction between cumulative exposures to neighborhood disadvantage and lead contamination. Specifically, we first estimate these effects using a model with the following form:

$$E\left(Y|\mathbf{C},\underline{\mathbf{L}},\underline{\mathbf{A}},\underline{\mathbf{M}}\right) = \eta_0 + \eta_1^T \mathbf{C}^{\perp} + \eta_2^T \sum_t \mathbf{L}_t^{\perp} + \gamma\text{avg}\left(\underline{\mathbf{A}}\right) + \theta\text{avg}\left(\underline{\mathbf{M}}\right) + \rho\left(\text{avg}\left(\underline{\mathbf{A}}\right) \times \text{avg}\left(\underline{\mathbf{M}}\right)\right),$$

where $\text{avg}\left(\underline{\mathbf{A}}\right) \times \text{avg}\left(\underline{\mathbf{M}}\right)$ is a conventional cross product term and ρ captures an interaction effect between neighborhood poverty and lead contamination. Under this model and the assumption of joint sequential ignorability, the controlled direct and mediator effects are given by the following parametric expressions:

$$CDE\left(\underline{\mathbf{a}},\underline{\mathbf{a}}',\underline{\mathbf{m}}\right) = \left(\gamma + \rho\text{avg}\left(\underline{\mathbf{m}}\right)\right)\left[\text{avg}\left(\underline{\mathbf{a}}\right) - \text{avg}\left(\underline{\mathbf{a}}'\right)\right] \text{ and}$$

$$CME\left(\underline{\mathbf{m}},\underline{\mathbf{m}}',\underline{\mathbf{a}}\right) = \left(\theta + \rho\text{avg}\left(\underline{\mathbf{a}}\right)\right)\left[\text{avg}\left(\underline{\mathbf{m}}\right) - \text{avg}\left(\underline{\mathbf{m}}'\right)\right],$$

where the controlled direct effect may now vary as a function of lead contamination, and the controlled mediator effect may vary as a function of neighborhood disadvantage.

In addition to this conventional approach to modeling interaction, we also estimate the controlled direct and mediator effects using a generalized additive model. This model can be expressed as follows:

$$E\left(Y|\mathbf{C},\underline{\mathbf{L}},\underline{\mathbf{A}},\underline{\mathbf{M}}\right) = \eta_0 + \eta_1^T \mathbf{C}^{\perp} + \eta_2^T \sum_t \mathbf{L}_t^{\perp} + f\left(\text{avg}\left(\underline{\mathbf{A}}\right),\text{avg}\left(\underline{\mathbf{M}}\right)\right),$$

where $f\left(\text{avg}\left(\underline{\mathbf{A}}\right),\text{avg}\left(\underline{\mathbf{M}}\right)\right)$ represents a tensor product spline that is capable of capturing complex forms of interaction and nonlinearity (Wood 2006). With this approach, the effects of interest do not have a simple parametric form and are estimated using the method of g-computation (Robins 1986; Snowden et al. 2011).

Figure A.1 displays estimates based on both of these modeling approaches. The first column contains estimates of the $CDE(\underline{\mathbf{a}}, \underline{\mathbf{a}}', \underline{\mathbf{m}})$ plotted over values of $\text{avg}(\underline{\mathbf{m}}) = m$, while the second column contains estimates of the $CME(\underline{\mathbf{m}}, \underline{\mathbf{m}}', \underline{\mathbf{a}})$ plotted over values of $\text{avg}(\underline{\mathbf{a}}) = a$. Results in the upper panel come from the linear model with a cross product interaction. In the lower panel, results are from the generalized additive model with a tensor product interaction. Both sets of results provide no evidence of effect interaction—that is, estimates of the $CDE(\underline{\mathbf{a}}, \underline{\mathbf{a}}', \underline{\mathbf{m}})$ and $CME(\underline{\mathbf{m}}, \underline{\mathbf{m}}', \underline{\mathbf{a}})$ are essentially invariant across levels of $\text{avg}(\underline{\mathbf{m}}) = m$ and $\text{avg}(\underline{\mathbf{a}}) = a$, respectively.

References

Robins, J. M. (1986). "A New Approach to Causal Inference in Mortality Studies with a Sustained Exposure period—Application to Control of the Healthy Worker Survivor Effect." *Mathematical Modelling* 7:9-12.

Snowden, J. M., Rose, S., & Mortimer, K. M. (2011). "Implementation of G-computation on Simulated Data Set: Demonstration of a Causal Inference Technique." *American Journal of Epidemiology* 173:731-738.

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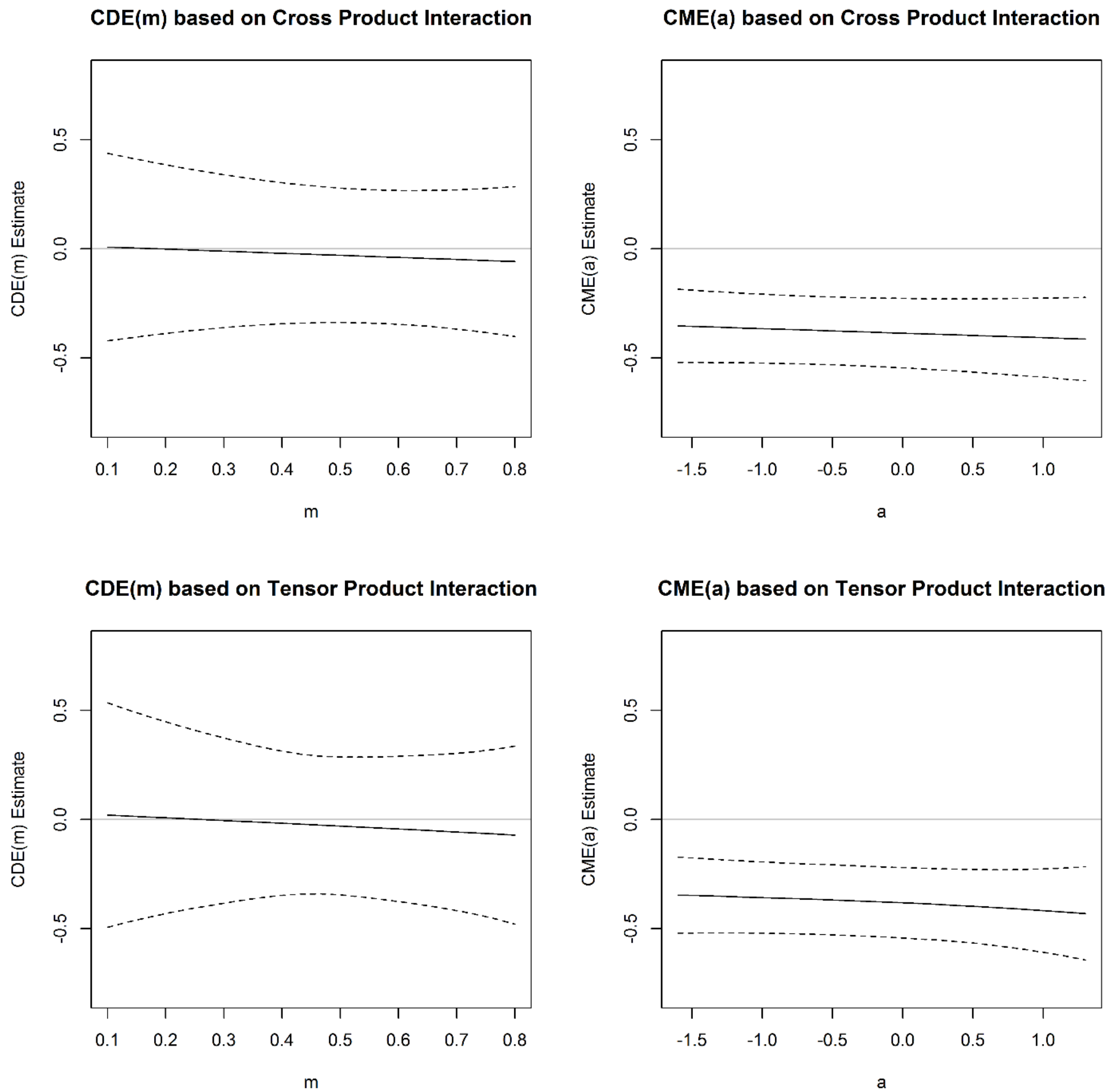

Figure A.1. Estimates of controlled direct and mediator effects from models that allow exposure-mediator interaction, Project on Human Development in Chicago Neighborhoods birth cohort (n=1266).
Notes: Dashed lines represent 95% confidence intervals based on the stratified cluster bootstrap with 250 replications.

Part B: Cumulative Effects from Models that allow Separate Coefficients by Wave

In this section, we report effect estimates from models that incorporate separate coefficients at each wave for exposure to neighborhood disadvantage and lead contamination. Specifically, we estimate the total effect using a model with the following form:

$$E\left(Y|\mathbf{C},\underline{\mathbf{L}},\underline{\mathbf{A}},\underline{\mathbf{M}}\right) = \alpha_0 + \alpha_1^T\mathbf{C}^{\perp} + \alpha_2^T\sum_t \mathbf{L}_t^{\perp} + \sum_t \beta_t A_t + \alpha_3 \sum_t M_t^{\perp},$$

where $ATE\left(\underline{\mathbf{a}},\underline{\mathbf{a}}'\right) = \sum_t \beta_t(a_t - a_t')$ under the assumptions of correct model specification and sequential ignorability. Similarly, we estimate the joint effects of interest using a model that can be expressed as follows:

$$E\left(Y|\mathbf{C},\underline{\mathbf{L}},\underline{\mathbf{A}},\underline{\mathbf{M}}\right) = \eta_0 + \eta_1^T\mathbf{C}^{\perp} + \eta_2^T\sum_t \mathbf{L}_t^{\perp} + \sum_t \gamma_t A_t + \sum_t \theta_t M_t,$$

where $CDE\left(\underline{\mathbf{a}},\underline{\mathbf{a}}'\right) = \sum_t \gamma_t(a_t - a_t')$, $CME\left(\underline{\mathbf{m}},\underline{\mathbf{m}}'\right) = \sum_t \theta_t(m_t - m_t')$ and the $AJE\left(\underline{\mathbf{a}},\underline{\mathbf{a}}',\underline{\mathbf{m}},\underline{\mathbf{m}}'\right)$ is equal to the sum of the controlled direct and mediator effects under assumptions outlined previously. In contrast to the models prioritized in the main text, the models described here do not constrain the effects of the exposure and mediator to be invariant over time.

We fit these more complex models using three variants of RWR. First, we implement RWR conventionally using least squares, as in the main text. Second, in an attempt to reduce the imprecision arising from collinearity between intertemporal measures of the exposure and mediator, we additionally implement RWR using the least absolute shrinkage and selection operator (LASSO; Tibshirani 1996) and the elastic net (Zou and Hastie 2005), with hyperparameters tuned using a grid search and $k = 10$ fold cross-validation. The LASSO and elastic net are regularization methods that can improve the accuracy of estimates when predictors are highly correlated, although this improvement arises from a bias-variance trade-off.

Table B.1 reports estimates for the cumulative effects of interest based on conventional RWR, RWR with LASSO regularization, and RWR with elastic net regularization. Although these estimates are based on more flexible models fit using several alternative methods, they target exactly the same quantities on which we focus in the main text. That is, the total and controlled direct effects in Table B.1 compare continuous residence in a neighborhood that is 0.7 standard deviations above the citywide mean on our index of concentrated disadvantage rather than a neighborhood that is 0.9 standard deviations below the mean. And the controlled mediator effect compares continuous residence in neighborhoods with an elevated blood lead prevalence rate of 65% rather than 30%. Across all three approaches to estimation, the results of this analysis are substantively similar and closely align with those based on the simpler models prioritized in the main text. This further suggests that our key inferences are highly robust to alternative specifications and estimation procedures.

References

Tibshirani, R. (1996). "Regression Shrinkage and Selection via the LASSO." *Journal of the Royal Statistical Society - Series B (Methodology)* 58:267-288.

Zou, H., & Hastie, T. (2005). "Regularization and Variable Selection via the Elastic Net." *Journal of the Royal Statistical Society - Series B (Methodology)* 67:301-320.

Table B.1. Estimated effects of cumulative exposure to neighborhood disadvantage and environmental lead contamination during early childhood on receptive vocabulary ability from models with separate coefficients for the exposure and mediator at each wave of follow-up, Project on Human Development in Chicago Neighborhoods birth cohort (n=1266)

Estimand	RWR		RWR + LASSO regularization		RWR + elasticnet regularization	
	est.	p-value	est.	p-value	est.	p-value
Average total effect (ATE)	-0.380 (0.106)	<0.001	-0.438 (0.100)	<0.001	-0.437 (0.098)	<0.001
Average joint effect (AJE)	-0.431 (0.104)	<0.001	-0.489 (0.096)	<0.001	-0.491 (0.095)	<0.001
Controlled direct effect (CDE)	-0.051 (0.162)	0.752	-0.155 (0.125)	0.214	-0.155 (0.121)	0.199
Controlled mediator effect (CME)	-0.380 (0.138)	0.006	-0.335 (0.115)	0.004	-0.335 (0.112)	0.003
Test for mediation (ATE - CDE)	-0.329 (0.123)	0.007	-0.283 (0.101)	0.005	-0.282 (0.097)	0.004

Notes: Results are combined estimates from 50 imputations. Standard errors in parentheses are computed using the stratified cluster bootstrap with 250 replications, and p-values are from z-tests of the null hypothesis that the focal estimand is equal to zero.

Part C: Falsification Test among Older Cohorts in the PHDCN

In this section, we perform a falsification test by evaluating whether neighborhood effects on cognitive ability are mediated by lead contamination among older children, who are less sensitive to lead contamination than are infants and toddlers. Although there is no age at which lead exposure is considered safe, children older than 6 years are at lower risk of cognitive impairment when exposed to an environment contaminated by lead at the levels typically observed in Chicago (ATSDR 2019). Thus, if our focal mediator were truly unconfounded, we would expect any evidence of mediation via lead contamination among older children to be less pronounced compared with the birth cohort. Alternatively, the appearance of strong mediation effects among older children would suggest that the same effects we document during early childhood may actually reflect other potentially confounding mechanisms, such as limited access to medical or public health services, as opposed to lead exposure per se.

To implement this falsification test, we replicate our analysis described in the main text on all $n = 2{,}628$ children in the 6, 9, and 12 year old cohorts from the PHDCN. Aside from the focus on older children, this replication differs from our analysis of the birth cohort in only one other respect: it uses a different measure of cognitive ability because older cohorts in the PHDCN were never administered the PPVT, and the PPVT was the only cognitive assessment given to the birth cohort. Specifically, in our analysis of the 6 to 12 year old cohorts, we use standardized scores on the Wechsler Intelligence Scale for Children-Revised vocabulary subtest (WISC-R; Wechsler 1974), which measures a similar construct, is highly correlated with the PPVT (Hodapp and Gerken 1999), and has previously been used in studies of both neighborhood effects (Sampson et al. 2008) and subclinical lead toxicity (Lanphear 2005).

Results from this parallel analysis are presented in Table C.1. Estimates for both the total and joint effects are substantively large, statistically significant, and comparable to those among the birth cohort reported in the main text. Estimates for the controlled direct and mediator effects, by contrast, differ markedly from those among the birth cohort. Specifically, among children age 6 to 12 years at baseline in the PHDCN, estimates for the controlled direct effect are substantively large and statistically significant, while estimates for the controlled mediator effect are close to zero. Thus, among older children, there is little evidence of mediation via lead contamination, and it would therefore appear that the effects of neighborhood poverty on vocabulary skills operate through different mechanisms at more advanced developmental stages. These findings disconfirm the falsification test and buttress our inferences about causal mediation via lead contamination during early childhood. Moreover, they are consistent with our theoretical model highlighting the special importance of environmental health hazards during early childhood and with our conclusions that attention to the developmental specificity of different putative mediators is critically important when studying neighborhood effects.

It is important to note, however, that this analysis does not represent a *pure* falsification test. Although children age 6 and older are less sensitive to lead contamination than infants and toddlers, they are not entirely insensitive. Indeed, lead exposure at levels that were rare but still occasionally observed in Chicago during the 1990s can be neurotoxic even for adults. Thus, our theoretical model, together with prior research on lead neurotoxicity, suggests only that neighborhood effect mediation via lead will be less pronounced among older children and not necessarily absent altogether. Our results are also consistent with this more nuanced prediction, even though we uncover essentially no evidence of mediation among older children, because the span of our interval estimates show that we cannot rule out the possibility of a comparatively small effect for lead contamination at more advanced development periods.

<u>References</u>

ATSDR. (2019). *Toxicological Profile for Lead*. Atlanta, GA: Agency for Toxic Substances and Disease Registry.

Hodapp, A. F., & Gerken, K. C. (1999). "Correlations between Scores for the Peabody Picture Vocabulary Test and the Wechsler Intelligence Scale for Children." *Psychological Reports* 84:1139-1142.

Lanphear, B. P., Hornung, R., Khoury, J., Yolton, K., Baghurst, P., & Bellinger, D. C., et al. (2005). "Low-Level Environmental Lead Exposure and Children's Intellectual Function: An International Pooled Analysis." *Environmental Health Perspectives* 113(7):894-999.

Sampson, R. J., Sharkey, P., & Raudenbush, S. W. (2008). "Durable Effects of Concentrated Disadvantage on Verbal Ability of among African-American Children." *Proceedings of the National Academy of Sciences* 105:845-852.

Wechsler, D. (1974). *Wechsler Intelligence Scale for Children (Revised Edition)*. San Antonio, TX: The Psychological Corporation.

Table C.1. Estimated effects of cumulative exposure to neighborhood disadvantage and environmental lead contamination during late childhood and adolescence on WISC-R vocabularly subtest scores, Project on Human Development in Chicago Neighborhoods six, nine, and twelve year old cohorts (n=2628)

Estimand	Linear and additive RWR		RWR + gender moderation		RWR + race moderation		RWR + income moderation	
	est.	p-value	est.	p-value	est.	p-value	est.	p-value
Average total effect (ATE)	-0.331 (0.072)	<0.001	-0.330 (0.071)	<0.001	-0.329 (0.072)	<0.001	-0.325 (0.072)	<0.001
Average joint effect (AJE)	-0.329 (0.073)	<0.001	-0.327 (0.073)	<0.001	-0.320 (0.074)	<0.001	-0.320 (0.074)	<0.001
Controlled direct effect (CDE)	-0.352 (0.119)	0.003	-0.349 (0.119)	0.003	-0.354 (0.121)	0.004	-0.363 (0.122)	0.003
Controlled mediator effect (CME)	0.024 (0.110)	0.829	0.023 (0.109)	0.836	0.034 (0.111)	0.761	0.043 (0.113)	0.706
Test for mediation (ATE - CDE)	0.021 (0.096)	0.826	0.020 (0.095)	0.835	0.026 (0.098)	0.794	0.038 (0.099)	0.704

Notes: Results are combined estimates from 50 imputations. Standard errors in parentheses are computed using the stratified cluster bootstrap with 250 replications, and p-values are from z-tests of the null hypothesis that the focal estimand is equal to zero.

Part D: Effects of Point-in-time Exposures

In the main text, we focus on the effects of cumulative exposures to a sequence of neighborhood conditions. Cumulative effects provide the most relevant test of our theoretical model, which concerns the influence of residential contexts throughout early childhood. Nevertheless, researchers and policymakers may also be interested in identifying sensitive periods during early childhood where they might target interventions. In this section, we attempt to shed some initial light on the question of sensitive exposure periods by analyzing the effects of point-in-time exposures to neighborhood disadvantage and environmental lead contamination during infancy (wave 1), the "toddler years" (wave 2), and the "pre-school years" (wave 3).

Specifically, we first consider the average total effect for a point-in-time exposure to different levels of neighborhood disadvantage at time t, which can be formally defined as follows:

$$ATE_t(a_t, a_t') = E\big(Y(a_t) - Y(a_t')\big).$$

This effect represents the expected difference in vocabulary ability if children were exposed at time t to the neighborhood conditions defined by a_t rather than a_t'. Following our analysis of cumulative effects in the main text, we model the $ATE_t(a_t, a_t')$ using a simple linear function, $ATE_t(a_t, a_t') = \beta_t(a_t - a_t')$.

We also consider the joint effects of point-in-time exposures to neighborhoods of different socioeconomic composition and with different levels of lead contamination, which are defined and modeled as follows:

$$AJE_t(a_t, a_t', m_t, m_t') = E\big(Y(a_t, m_t) - Y(a_t', m_t')\big) = \gamma_t(a_t - a_t') + \theta_t(m_t - m_t').$$

The $AJE_t(a_t, a_t', m_t, m_t')$ is the expected difference in vocabulary ability if children were exposed at time t to the neighborhood conditions and lead contamination given by $\{a_t, m_t\}$

rather than $\{a_t', m_t'\}$. Under a linear and additive model for the $AJE_t(a_t, a_t', m_t, m_t')$, this effect can be separated into the sum of a controlled direct effect of neighborhood composition at time t and a controlled mediator effect of lead contamination at time t. Specifically, point-in-time variants of the controlled direct and mediator effects are given by

$$CDE_t(a_t, a_t') = E\big(Y(a_t, m_t) - Y(a_t', m_t)\big) = \gamma_t(a_t - a_t') \text{ and}$$

$$CME_t(m_t, m_t') = E\big(Y(a_t, m_t) - Y(a_t, m_t')\big) = \theta_t(m_t - m_t').$$

All of these effects are similar to those prioritized in the main text except that they involve differences in exposures to neighborhood poverty and environmental lead contamination at a single point in time instead of cumulatively throughout early childhood.

The total effect at time t can be identified if the following ignorability assumption holds at the same time period:

$$Y(a_t) \perp A_t | \mathbf{C}, \underline{\mathbf{L}}_t, \underline{\mathbf{A}}_{t-1}, \underline{\mathbf{M}}_{t-1},$$

where $\perp$ denotes statistical independence, A_t denotes a child's observed exposure to neighborhood disadvantage at time t, $\underline{\mathbf{A}}_{t-1}$ and $\underline{\mathbf{M}}_{t-1}$ respectively denote a child's observed history of exposure to neighborhood disadvantage and environmental lead through time $t-1$, $\underline{\mathbf{L}}_t$ denotes a child's history of time-varying covariates through time t, and $\mathbf{C}$ denotes the vector of baseline controls. The joint, controlled direct, and controlled mediator effects at time t can be identified under the following set of two ignorability assumptions:

$$Y(a_t, m_t) \perp A_t | \mathbf{C}, \underline{\mathbf{L}}_t, \underline{\mathbf{A}}_{t-1}, \underline{\mathbf{M}}_{t-1}$$

$$Y(a_t, m_t) \perp M_t | \mathbf{C}, \underline{\mathbf{L}}_t, \underline{\mathbf{A}}_t, \underline{\mathbf{M}}_{t-1},$$

where all terms are defined as above. In words, these assumptions require that exposure to both neighborhood poverty and a lead-contaminated environment are not confounded by unobserved factors at time t, conditional on the observed past.

We estimate the total effect at time t using a linear model with the following form:

$$E(Y|\mathbf{C},\underline{\mathbf{L}}_t,\underline{\mathbf{A}}_t,\underline{\mathbf{M}}_{t-1}) = \alpha_0 + \alpha_1^T\mathbf{C} + \sum_{j=1}^{t}\omega_j^T\mathbf{L}_j + \sum_{j=1}^{t}\beta_j A_j + \sum_{j=1}^{t-1}\alpha_j M_j,$$

where, at time $t = 1$, $\underline{M}_{t-1}$ is empty and therefore excluded. Similarly, we estimate the joint, controlled direct, and controlled mediator effects at time t using another linear model, which can be expressed as follows:

$$E(Y|\mathbf{C},\underline{\mathbf{L}}_t,\underline{\mathbf{A}}_t,\underline{\mathbf{M}}_t) = \alpha_0 + \alpha_1^T\mathbf{C} + \sum_{j=1}^{t}\omega_j^T\mathbf{L}_j + \sum_{j=1}^{t}\gamma_j A_j + \sum_{j=1}^{t}\theta_j M_j.$$

These models differ from those we use to estimate cumulative effects in that they do not adjust for residual transformations of the covariates. This is because the focus on point-in-time rather than cumulative effects obviates the need to adjust for biases arising from improper control of time-varying confounders. If these models are correctly specified and the identification assumptions outlined previously are satisfied at time t, then least squares estimates of $\beta_t(a_t - a_t')$, $\gamma_t(a_t - a_t')$, and $\theta_t(m_t - m_t')$ are consistent and asymptotically normal for the $ATE_t(a_t, a_t')$, $CDE_t(a_t, a_t')$, and $CME_t(m_t, m_t')$, respectively.

In this analysis, identification of effects at time t requires adjusting for the observed past through time t, including prior measures of the exposure and mediator. As a result, least squares estimates at time $t = 2$ (the toddler years) and $t = 3$ (the pre-school years) suffer from considerable imprecision due to collinearity between contemporaneous and lagged measures of the exposure and mediator. For example, pairwise correlations between measures taken at different waves range from 0.77 to 0.87 for concentrated disadvantage and from 0.80 to 0.88 for lead contamination. This limits our ability to precisely estimate the effects of point-in-time exposures beyond the baseline time period. Thus, in an attempt to improve precision, we estimate point-in-time effects not only by the method of least squares but also using the least absolute shrinkage and selection operator (LASSO; Tibshirani 1996) and the elastic net (Zou and

Hastie 2005). As mentioned previously, the LASSO and elastic net are regularization methods that can improve the accuracy of estimates when predictors are highly correlated. We tune the hyperparameters of these estimation procedures using a grid search and $k = 10$ fold cross-validation.

With all methods, we estimate total and controlled direct effects that compare residence at time t in a neighborhood that is 0.7 standard deviations above the citywide mean on our index of concentrated disadvantage rather than a neighborhood that is 0.9 standard deviations below the mean. And when evaluating the controlled mediator effect, we compare residence at time t in neighborhoods with an elevated blood lead prevalence rate of 65% rather than 30%. In this way, we focus on a set of point-in-time effects that are based on contrasts similar to those upon which the cumulative effects are based in the main text.

Tables D.1, D.2, and D.3 present estimates of point-in-time effects during infancy ($t = 1$), the toddler years ($t = 2$), and the pre-school years ($t = 3$), respectively. In Table D.1, estimates of point-in-time effects during infancy are similar to the cumulative effect estimates reported in the main text—specifically, there is strong evidence that exposure to neighborhood disadvantage at this development stage reduces cognitive ability because of differences in exposure to lead. In Tables D.2 and D.3, estimates of point-in-time effects during the toddler and pre-school years follow a pattern loosely resembling that during infancy, but they are much less pronounced and suffer from considerable sampling error due to collinearity among contemporaneous and lagged measures of the exposure and mediator. Taken together, these results mainly indicate that we lack the data needed to clearly identify sensitive exposure periods during early childhood, but what little evidence the PHDCN is able to provide on this matter suggests that exposures during infancy may be particularly consequential.

References

Tibshirani, R. (1996). “Regression Shrinkage and Selection via the LASSO.” *Journal of the Royal Statistical Society - Series B (Methodology)* 58:267-288.

Zou, H., & Hastie, T. (2005). “Regularization and Variable Selection via the Elastic Net.” *Journal of the Royal Statistical Society - Series B (Methodology)* 67:301-320.

Table D.1. Estimated effects of point-in-time exposures to neighborhood disadvantage and environmental lead contamination during infancy (wave 1) on end-of-study receptive vocabulary ability, Project on Human Development in Chicago Neighborhoods birth cohort (n=1266)

Estimand	Linear Model (LM)		LM + LASSO regularization		LM + elasticnet regularization	
	est.	p-value	est.	p-value	est.	p-value
Average total effect (ATE_1)	-0.345 (0.090)	<0.001	-0.381 (0.087)	<0.001	-0.376 (0.084)	<0.001
Average joint effect (AJE_1)	-0.388 (0.091)	<0.001	-0.429 (0.084)	<0.001	-0.428 (0.083)	<0.001
Controlled direct effect (CDE_1)	-0.124 (0.123)	0.313	-0.146 (0.114)	0.197	-0.153 (0.104)	0.142
Controlled mediator effect (CME_1)	-0.264 (0.112)	0.018	-0.283 (0.107)	0.008	-0.275 (0.098)	0.005
Test for mediation (ATE_1 - CDE_1)	-0.221 (0.097)	0.022	-0.235 (0.091)	0.010	-0.224 (0.082)	0.006

Notes: Results are combined estimates from 50 imputations. Standard errors in parentheses are computed using the stratified cluster bootstrap with 250 replications, and p-values are from z-tests of the null hypothesis that the focal estimand is equal to zero.

Table D.2. Estimated effects of point-in-time exposures to neighborhood disadvantage and environmental lead contamination during the toddler years (wave 2) on end-of-study receptive vocabulary ability, Project on Human Development in Chicago Neighborhoods birth cohort (n=1266)

Estimand	Linear Model (LM)		LM + LASSO regularization		LM + elasticnet regularization	
	est.	p-value	est.	p-value	est.	p-value
Average total effect (ATE_2)	0.008 (0.116)	0.947	-0.034 (0.073)	0.643	-0.036 (0.072)	0.620
Average joint effect (AJE_2)	-0.066 (0.128)	0.606	-0.123 (0.109)	0.260	-0.124 (0.105)	0.238
Controlled direct effect (CDE_2)	0.192 (0.171)	0.261	-0.004 (0.042)	0.932	-0.004 (0.043)	0.928
Controlled mediator effect (CME_2)	-0.258 (0.177)	0.146	-0.119 (0.108)	0.270	-0.120 (0.103)	0.244
Test for mediation (ATE_2 - CDE_2)	-0.184 (0.129)	0.153	-0.030 (0.063)	0.633	-0.032 (0.062)	0.605

Notes: Results are combined estimates from 50 imputations. Standard errors in parentheses are computed using the stratified cluster bootstrap with 250 replications, and p-values are from z-tests of the null hypothesis that the focal estimand is equal to zero.

Table D.3. Estimated effects of point-in-time exposures to neighborhood disadvantage and environmental lead contamination during the pre-school years (wave 3) on end-of-study receptive vocabulary ability, Project on Human Development in Chicago Neighborhoods birth cohort (n=1266)

Estimand	Linear Model (LM)		LM + LASSO regularization		LM + elasticnet regularization	
	est.	p-value	est.	p-value	est.	p-value
Average total effect (ATE_3)	-0.154 (0.139)	0.268	-0.089 (0.101)	0.377	-0.089 (0.101)	0.377
Average joint effect (AJE_3)	-0.191 (0.153)	0.210	-0.148 (0.118)	0.212	-0.141 (0.112)	0.208
Controlled direct effect (CDE_3)	-0.086 (0.192)	0.656	-0.035 (0.083)	0.673	-0.036 (0.080)	0.648
Controlled mediator effect (CME_3)	-0.106 (0.194)	0.584	-0.113 (0.118)	0.338	-0.105 (0.112)	0.351
Test for mediation (ATE_3 - CDE_3)	-0.069 (0.126)	0.585	-0.054 (0.073)	0.455	-0.053 (0.076)	0.487

Notes: Results are combined estimates from 50 imputations. Standard errors in parentheses are computed using the stratified cluster bootstrap with 250 replications, and p-values are from z-tests of the null hypothesis that the focal estimand is equal to zero.

Part E: Changes in Lead Contamination over Time in Chicago

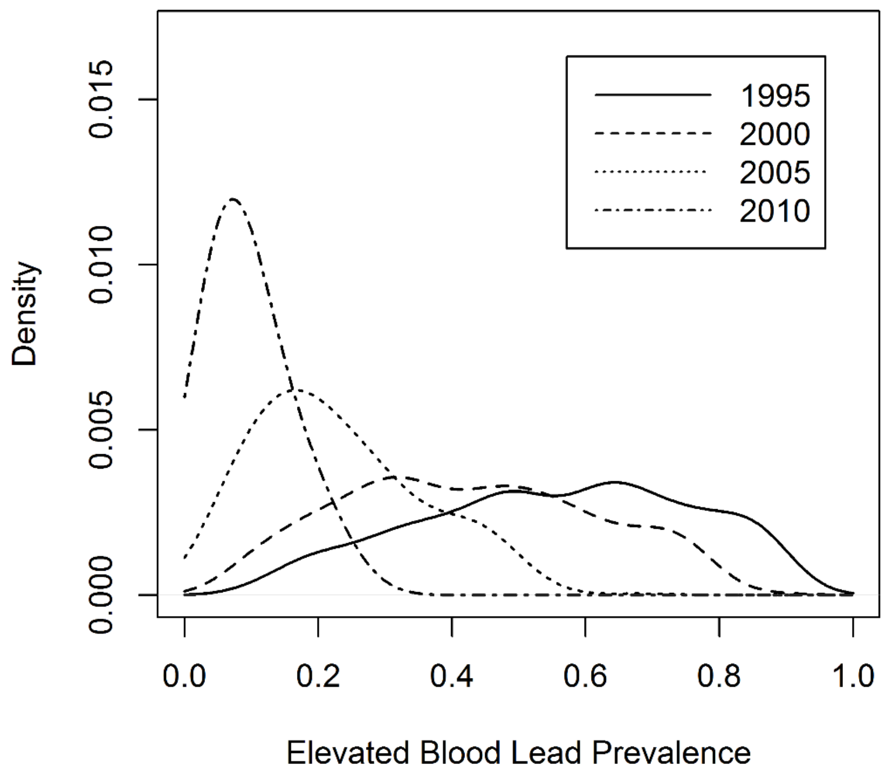

Figure E.1. Temporal Changes in Environmental Lead Contamination among Chicago Neighborhoods, 1995-2010.
Notes: This plot contains kernel densities computed over all neighborhood clusters in Chicago for a given year.