Environ Health Perspect

DOI: 10.1289/EHP5838

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Supplemental Material

A Quantile-Based g-Computation Approach to Addressing the Effects of Exposure Mixtures

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Additional File- Supplemental Code and Data Files