Proposed Approach for Developing Lead Dust Hazard Standards for Residences

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1. Introduction

TSCA section 403 directs EPA to promulgate regulations that identify, for the purposes of Title X and Title IV of TSCA, dangerous levels of lead in paint, dust, and soil. EPA promulgated regulations pursuant to TSCA section 403 on January 5, 2001, and codified them at 40 CFR part 745, subpart D (USEPA, 2001a). These hazard standards identify dangerous levels of lead in paint, dust, and soil and provide benchmarks on which to base remedial actions taken to safeguard children and the public from the dangers of lead. Lead-based paint hazards in target housing and child-occupied facilities are defined in these standards as paint-lead, dust-lead, and soil-lead hazards. A paint-lead hazard is defined as any damaged or deteriorated lead-based paint, any chewable lead-based painted surface with evidence of teeth marks, or any lead-based paint on a friction surface if lead dust levels underneath the friction surface exceed the dust-lead hazard standards. A dust-lead hazard is surface dust that contains a mass-per-area concentration of lead equal to or exceeding 40 micrograms per square foot ($\mu g/ft^2$) on floors or 250 $\mu g/ft^2$ on interior window sills based on wipe samples. A soil-lead hazard is bare soil that contains total lead equal to or exceeding 400 parts per million (ppm) in a play area or average of 1,200 ppm of bare soil in the rest of the yard based on soil samples.

On August 10, 2009, EPA received a petition from several environmental and public health advocacy groups requesting that the EPA amend regulations issued under Title IV of TSCA (Sierra Club et al., 2009). Specifically, the petitioners requested that EPA lower the Agency's dust-lead hazard standards issued pursuant to section 403 of TSCA from 40 µg/ft2 to 10 µg/ft2 or less for floors and from 250 µg/ft2 to 100 µg/ft2 or less for window sills. On October 22, 2009, EPA granted this petition under section 553(e) of the Administrative Procedures Act, 5 U.S.C. 553(e) (USEPA, 2009a). In granting this petition, EPA agreed to commence the appropriate proceeding, but did not commit to a particular schedule or to a particular outcome.

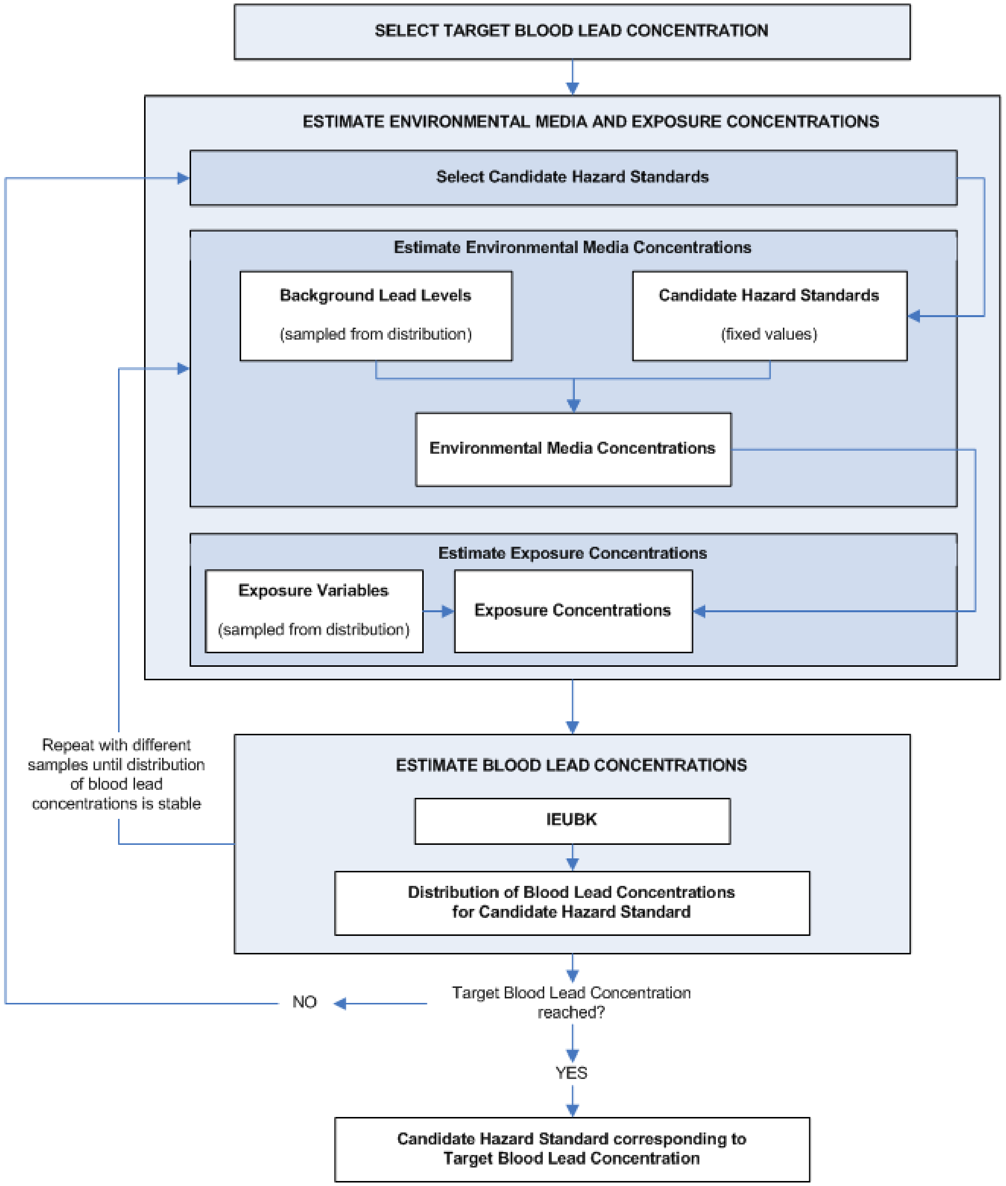
This document describes the proposed approach for developing dust-lead hazard standards for floors and window sills in residences. Figure 1-1 provides an overview of the approach for developing hazard standards for residences. The approach is made up of three primary steps:

- Select target blood lead concentration
- Estimate environmental media and exposure concentrations; and
- Estimate blood lead concentrations.

The first step, ***Select Target Blood Lead Concentration***, involves the selection of target blood lead levels. The proposed approach for residential hazard standards will focus on target blood lead levels that are associated with IQ effects in children; three target blood lead levels have been selected which are at the low end of the dose-response curve. The remaining steps of the approach will then be applied to estimate the candidate dust-lead levels (hazard standards) for floors and window sills that do not result in blood lead levels exceeding the target levels in children.

The second step, ***Estimate Environmental Media and Exposure Concentrations***, involves characterizing lead concentrations in relevant environmental media and using these data, in conjunction with information about human behavior patterns, to estimate lead exposures. This step consists of three parts: selecting dust-lead levels for window sills and floors (candidate hazard standards), estimating environmental media concentrations, and estimating exposure concentrations.

Figure 1-1. Overview of Approach for Developing Hazard Standards for Residences



This process would be repeated for each target blood lead concentration.

The Floor Dust Loading for Residences is assigned a fixed value (i.e., candidate hazard standard) for each simulation. A candidate hazard standard for Window Sill Dust Loading for Residences is then estimated by an equation relating floor to window dust loading.

All other media are sampled from distributions of background

Environmental media concentrations are assumed not to vary with time.

Exposure variables are used to define where individuals spend time and how long they spend in each location, as well as ingestion rates for soil/dust, water, and diet.

Exposure concentrations are calculated based on the exposure variables and the relevant environmental media concentrations. Unlike the environmental media concentrations, which are assumed to be constant, exposure concentrations will vary across ages (for children under 6).

Each realization (i.e., repetition of Monte Carlo sampling) of exposure variables and background lead, along with the fixed candidate hazard standard, will be used to generate exposure concentrations and then a blood lead concentration using IEUBK. The resulting blood lead concentrations for all realizations will be used to generate a probability distribution of blood lead concentrations for the candidate hazard standard.

- *Select candidate hazard standard*. For each selected potential blood lead level of concern, an initial candidate hazard standard for floor dust loading will be selected and carried through the remaining steps of the approach. The candidate hazard standard for window sill dust loading will be calculated based on the candidate hazard standard for floor loading using an estimated relationship between floor dust and window sill dust loadings.
- *Estimate environmental media concentrations*. The approach uses total blood lead concentrations, rather than incremental concentrations attributable to different hazard standards, and as such, it requires estimates of lead concentrations for all relevant environmental media, rather than only focusing on lead concentrations on floors and window sills. To account for the variability in lead concentrations in other environmental media in the U.S., the approach will apply Monte Carlo sampling of distributions of background lead. To simplify the approach, it is assumed that environmental media concentrations will not change with time.
- *Estimate exposure concentrations*. Exposure concentrations are estimated by combining information about the lead concentrations in different environmental media with information about where the population of interest is located at different times, what activities they are engaged in, and other information about their behavior. Children under age 6 were selected as the population of interest for this approach because they are considered the most susceptible population for IQ effects resulting from lead exposure. Distributions of exposure variables for this population are selected to roughly represent the range of exposures experienced in the U.S. by children under age 6. Therefore, environmental media concentrations are assumed to remain constant with time, while estimated exposure concentrations will change with children's ages to reflect behavior differences in development.
- The temporal patterns of exposure concentrations for children under age 6 will be developed using different exposure scenario characteristics for each year (0-1, 1-2, etc.). These exposure variables will be defined by distributions and Monte Carlo sampling will be applied to select values from these distributions. Distributions of the exposure variables related to children's activity (i.e., where they spend time and how long they spend in each location) are developed by analyzing human activity data from the Consolidated Human Activity Database (CHAD) (USEPA 2009b). Distributions of other exposure variables (e.g., soil/dust ingestion rate, water ingestion rate) are developed by analyzing data included in EPA's Child-Specific Exposure Factors Handbook (USEPA 2008a). Each age will be simulated separately to develop distributions of exposure concentrations for that age, and the resulting distributions of lead exposure concentrations for all modeled ages will serve as inputs to the blood lead modeling.

In the third step of the approach, ***Estimate Blood Lead Concentrations***, the distributions of exposure concentrations will be used to estimate a distribution of blood lead concentrations associated with several candidate hazard standards. As discussed further below, blood lead concentrations will be estimated using EPA's Integrated Exposure Uptake Biokinetic Model for Lead in Children (IEUBK). After sufficient samples have been simulated to develop a stable distribution of blood lead concentrations, the distribution's prespecified percentile blood lead concentration will be compared to the target concentration. If the estimate does not match the target (within the specified tolerance), a different candidate hazard standard for floor dust will be selected and the remaining steps of the approach will be repeated. This iterative process continues until candidate hazard standards for floor dust and window sill dust have been developed for each potential level of concern.

The subsequent sections of this document provide more detailed descriptions of the approach for residences (Sections 2 through 5) and present the key data needs for implementing the approach (Section 6).

2. Target Blood Lead Concentration

2.1. Selection of Endpoint

There is a strong consensus within the public health community that the adverse effects of lead exposure are greatest in children and that impairment of neurological development is the "critical effect" (the effect occurring at the lowest exposure levels) (USEPA 2006, CDC 2005, 2009a, Bellinger 2008, Lanphear et al. 2005). The intelligence quotient (IQ) is the most commonly measured neurodevelopmental endpoint in lead-exposed children, and blood lead is the most common exposure/dose metric in epidemiological studies. A number of recent studies (Canfield et al. 2003, Chiodo et al. 2004, Jusko et al. 2008, Lanphear et al. 2005, Miranda et al. 2007, Surkan et al. 2007, Téllez-Rojo et al. 2006) have reported decrements in IQ and other adverse effects at blood lead levels less than 10 µg/dL. It is generally agreed that no specific "threshold" blood lead level for adverse effects on IQ in children has been identified. In addition to IQ measures, there is rapidly accumulating evidence that lead also affects other aspects of neurological development, and that in many of these studies, these effects were also observed in children at blood lead levels less than 10 µg/dL. These studies are reviewed in USEPA (2006); more recent reports include an association between early lead exposure and increased incidence of ADHD (Nigg et al. 2008, 2010), ADHD coupled with other behavior problems (Roy et al. 2008), as well as additional observations of increased criminal behavior (Wright et al. 2008) and other behavioral problems in young children (Chen et al. 2007).

Although there are some uncertainties in using both blood lead as a measure of exposure and IQ changes as an outcome measure, it is more difficult to generalize the results of the more complex neurobehavioral effects identified above. Therefore, children's IQ has been chosen as the primary critical endpoint for determining the potential blood lead levels of concern. In making this choice, it is recognized that IQ effects do not capture the entire spectrum of adverse neurological effects associated with lead exposure in children. Estimating IQ loss thus represents a lower bound on the overall adverse effects of lead exposures to children.

2.2. Selection of Target Blood Lead Levels

For purposes of this Approach, a distribution for a hypothetical child will be modeled around individual candidate hazard standards. Blood lead levels of 1, 2.5 and 5 µg/dL have been chosen in order to evaluate a range of potential hazard standards. These levels were chosen, in part, based on recent literature which shows that increases in children's blood lead from 1 to 10 µg/dL result in a greater decrement in IQ score than increases from 10 to 20 µg/dL, or from 20 to 30 µg/dL (Lanphear et al. 2005; Canfield et al. 2003; Schwartz 1994). This finding indicates a steeper dose-response relationship at blood lead levels below 10 µg/dL. Lanphear et al. (2005) derived regression relationships between several blood lead metrics (lifetime, concurrent, peak and early childhood) and IQ test results. Several different models relating blood lead metrics to IQ, which predict a wide range of IQ changes for given blood lead levels, were used. First, they developed log-linear models relating IQ changes to all blood lead metrics they examined. In these models, the relationships between IQ change and blood lead are curved, with steeper slopes at low blood lead levels. Lanphear et al. (2005) also fit piecewise models (consisting of separate linear fits for different blood lead concentration ranges) to several of the blood lead metrics, and presented the results developed for the concurrent blood lead metric. EPA (U.S.EPA Activity-related Communication 2007) also obtained the relevant piecewise models for lifetime average blood lead concentrations based on the same data set.

For the blood lead metric, this approach is considering using both the lifetime and concurrent blood lead metrics. The peak blood lead metric was considered for this approach but ultimately not selected given the exposure scenario under consideration, which involved a relatively low-level, chronic exposure for the duration of the exposure period. Given that the approach does not include time-varying media concentrations, concurrent blood lead measures could be preferred because they would involve calculating an average for ages 5 or 6 years, which might result in higher blood lead levels than the lifetime average because it would allow for maximum accumulation of lead in the body. On the other hand, exposures are likely to be highest during the first two years of life, based on behavior patterns and amount of time spent in the residence, and as a result the lifetime average could be higher than the concurrent concentration. For this approach, it is proposed that both metrics be calculated for each candidate hazard standard and that the metric resulting in the overall higher blood lead level be selected to provide a basis for standards presentation.

3. Environmental Media and Exposure Concentrations

Lead exposures are characterized in this approach by combining environmental media concentrations with exposure variable data (e.g., human activity data, ingestion rates, respiration rates). Distributions of environmental media concentrations are developed from the available literature for all microenvironments expected to contribute to lead exposures (e.g., floor dust, soil, air). These distributions are sampled using Monte Carlo techniques, the lead dust loadings are converted to lead dust concentrations (Appendix A), and the environmental media concentrations for the microenvironments are time-weight averaged using the activity pattern information and combined with other exposure variable data to estimate exposure concentrations. This process is described in detail below.

3.1. Estimating Distributions of Concentrations in Each Microenvironment

For each microenvironment of interest, distributions of dust lead concentrations, soil lead concentrations, and air lead concentrations are required as inputs to the blood lead model. Each distribution will account for the expected variability of lead concentrations in the medium and should be nationally representative to the extent possible. Floor and window sill dust concentrations must be characterized separately because they are fixed based on the candidate hazard standards being evaluated. Table 3-1 shows for the residential hazard standard approach which media concentrations are needed in each microenvironment category. The assumption is made that while in a car, a child is not coming into contact with lead in dust or soil. In addition, exposure to soil is only included when the child is outdoors; soil is tracked into the indoor environment, but is accounted for as part of indoor dust; and the dust concentrations will be specifically developed to account for the tracked-in soil.

A literature search will be conducted to identify candidate data sources to represent each medium and microenvironment. Where possible, microenvironment categories will be divided according to particular lead exposure and the characteristics of children's activities in the microenvironments. However, if specific data are not available, microenvironments within a category will be combined to assure adequate data coverage. The available data will be examined and an appropriate distribution will be developed based on this information for each medium/microenvironment combination. In general, candidate distributions will be the normal distribution, the lognormal distribution, or the uniform distribution. Previous similar assessments (e.g., USEPA 2008b) have shown that many media concentration distributions are positively skewed and the lognormal distribution often is the most appropriate representative. The definition of each distribution will be an arithmetic mean and standard deviation (for normal distributions), a geometric mean and geometric standard deviation (for lognormal distributions), or a lower and upper cutoff (for uniform distributions).

Table 3-1. Media Concentration Distributions Needed for the Residential Hazard Standard Approach

Microenvironment Type	Dust Conc., Floors	Dust Conc., Window Sills	Soil Conc.	Air Conc.
Residence	The candidate floor hazard standard loading, converted to concentration	The candidate window sill hazard standard loading, converted to concentration	Not needed	Representative indoor air concentration
Commercial/ Public Buildings	Representative dust concentration (converted from dust loading if necessary)	Representative dust concentration (converted from dust loading if necessary)	Not needed	Representative indoor air concentration
Child-Occupied Facilities	Representative dust concentration (converted from dust loading if necessary)	Representative dust concentration (converted from dust loading if necessary)	Not needed	Representative indoor air concentration
Outdoors	Not needed	Not needed	Representative soil concentration	Representative ambient air concentration
Traveling	Not needed	Not needed	Not needed	Representative in- vehicle concentration compatible with near-roadway conditions

3.2. Estimating Environmental Media Concentrations

After the distributions have been defined, they will be used in an exposure model that utilizes Monte Carlo sampling techniques to characterize the variability in exposures. Specifically, each media concentration distribution will be sampled to estimate the total lead exposure of a hypothetical child (referred to as a Monte Carlo "realization"). This process will be repeated across numerous realizations, each modeling different hypothetical children, to develop a distribution of lead exposure concentrations across the modeled set of hypothetical children. The amount of time each of these hypothetical children spends in each microenvironment will be consistent with the activity patterns discussed in Section 3.4.1. The media concentrations for each microenvironment used for each hypothetical child will be sampled from the distributions, which results in each hypothetical child having an individualized set of environmental media concentrations.

The first step in estimating the environmental media concentrations is selecting the candidate hazard standards for floors and window sills in the residence. The candidate floor dust hazard standard is selected first and then the accompanying window sill candidate standard is estimated using a relationship between floor dust lead and window sill dust lead developed from empirical data. Because the floor and window sill loadings in a residence are expected to be correlated and because the hazard standard implementation will assume that both hazard standards are being met simultaneously in a residence, it is necessary to fix the candidate floor and window sill hazard standards simultaneously. Several data sets exist which could be used to derive an empirical relationship between the floor and window sill loadings, as discussed in Section 6.1.5.

Once the candidate hazard standards have been fixed, a set of Monte Carlo realizations will be simulated to capture the variability in environmental concentrations in the other exposure media. For each hypothetical child, pseudo-random numbers (referred to as "seeds") will be generated for each of the environmental media in Table 3-1. These seeds will be used to sample from the underlying distributions to generate the estimate of environmental media concentrations in each microenvironment for that realization. The only media concentrations that will not be sampled from distributions are residential floor and residential window sill, which are fixed based on the candidate hazard standards being evaluated.

The activity patterns change for each year of a child's life, as described in Section 3.4.1. The assumption is made, however, that the media concentrations in each microenvironment do not change significantly through time and that the type of microenvironment within each microenvironment category that the child visits does not change. Thus, the media concentrations are sampled once for each hypothetical child and these samples are used for all ages of that child's life. For example, a child may spend more time in the car at age 5 than at age 1, but the environmental lead concentration to which that child is exposed while in the car (but not necessarily the child's lead exposure, which is affected by such exposure factors as breathing rate) is assumed the same for both ages.

3.3. Converting Dust Lead Loading to Dust Lead Concentration

Each candidate hazard standard will be developed in terms of lead dust loading on the floor and window sill, in units of lead mass per unit area. In addition, many lead exposure data in the literature are reported as lead loadings (e.g., ug/ft^2) based on the total amount of lead mass collected in wipe or vacuum samples in a home. The blood lead models considered for this approach (discussed in Section 4), however, do not accept lead dust loadings as inputs. Instead, they require lead dust exposures to be in units of lead concentration (mass of lead per mass of dust). Thus, a method is needed to convert between the two in the development of the floor and window sill hazard standards. This analysis will consider two methods, developed specifically for the hazard standard estimation, to convert from lead dust loading to lead dust concentration: a statistical regression model and a mechanistic mass-balance model. An overview, including the strengths and weaknesses of each method, is provided in this section, and full details are provided for each in Appendix A.

The first method involves deriving a statistical relationship between observed lead dust loadings and lead dust concentrations in a nationally representative dataset. The HUD survey of lead in homes (USEPA 1995) contains average floor lead loadings from both wipe and vacuum samples as well as floor lead concentrations at approximately 280 homes. The survey was designed to be nationally representative and covers homes in four different vintage categories: Pre-1940, 1940-1959, 1960-1979, and Post-1980. Only the first three vintages are expected to include homes with lead-containing paint because in 1978 lead was restricted in residential paint by law. In order to focus on the relationship in homes with lead paint, data from the earlier three vintages were combined and a regression equation was developed to describe the relationship between lead loading and lead concentration. Because wipe samples tend to capture more of the existing lead dust and are not subject to vacuum collection inefficiencies, the wipe loading data were used to develop the relationship. In addition, both a linear regression and a regression between the natural log-transformed variables were performed, and the log-transformed data are described better by their regression coefficient (see Appendix A for more details). The final relationship between lead loading and lead concentration based on these data is:

$$Concen = 50.96 \times Loading^{0.6553}$$

The HUD data also contain information about the window sill dust loadings, but no window sill concentration information is available. Window sill loadings and concentrations are available from a Rochester, NY study (Lanphear et al. 1998a), and could be used to develop a regression equation for window sills. Unlike the HUD data, however, these data may not be representative of relationships between loadings and concentrations across the U.S., and they may introduce bias when compared with the HUD data.

In addition to this regression equation, a mechanistic mass-balance model was developed. This model accounts for the three dominant sources of lead to indoor dust: penetration of ambient air into the indoor environment, tracking of lead soil into the home, and flaking of lead-containing paint from walls. Removal occurs due to ventilation and routine cleaning. The model preserves the total mass in the system and accounts for the accumulation of both lead and particulate on the floor and in the indoor air. The particulate must be included in the model in order to calculate the lead dust concentration because the denominator of the concentration is total dust mass. Thus, in addition to the lead sources, there is also an indoor source of mass from cooking, smoking, and human dander that contributes to dust but is not expected to contain appreciable concentrations of lead. By converting the mass-balance differential equations to difference equations, the model can be integrated forward in time. For the hazard standard calculation, however, the dust levels are expected to be relatively constant in time and not to be subject to any short-term perturbations, such as renovation activities. Thus, the model equations can be solved directly for the steady-state solutions. These solutions provide total dust mass and total lead mass, and from these both the loading and concentration can be calculated. Thus, the steady-state solutions can be used to derive the slope in the equation:

$$Concen = \frac{1}{Slope} \times Loading$$

This slope is then given by (also derived as equation 3 in Appendix A):

$$\begin{aligned} slope = {} & \frac{1}{[(R + CE \times CF)(AER + D) - RD] \times V \times FloorLoading} \times \\ & [CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) + \\ & TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) + \\ & PartAir \times D \times AER \times P \times V + \\ & D \times (CookingRate + SmokingRate + DanderRate)] \end{aligned}$$

Where:

AER = air exchange rate ($hour^{-1}$)

P = penetration efficiency (unitless)

V = volume of the house (m^3)

D = deposition rate (h^{-1})
R = resuspension rate (h^{-1})
PbPaintConcen = lead concentration in the paint (mg/cm^2)
ChipFraction = fraction of total wall area which flakes from the walls per year (year^{-1})
WallLoading = area of wall space per unit volume of the home (m^2/m^3)
CoverageDens = the coverage density of paint on the wall (g/m^2)
UnitConv = unit conversion necessary to make units consistent 1 year/8760 h)
PbSoilConcen = concentration of lead in the tracked-in soil (µg/g)
TrackingRate = rate at which particulate is deposited on front mats (g/h)
MatFrac = fraction of total tracked material which is deposited on the front mat (as opposed to the remainder of the house) (unitless)
CE = cleaning efficiency (unitless)
CF = cleaning frequency (cleanings/h)
PartAIR = concentration of particulate in ambient air (g/m^3)
$CookingRate_{Part}$ = rate of generation of particulate mass due to cooking (g/h)
$SmokingRate_{Part}$ = rate of generation of particulate mass due to smoking (g/h)
$DanderRate_{Part}$ = rate of generation of particulate mass due to dander (g/h)

In this equation, most variables are set to their central tendency value when converting the loadings to concentrations. However, the slope is particularly sensitive to the cleaning frequency, house volume, and outdoor soil tracking rate, and distributions are available in the literature for each of these variables. Thus, for each hypothetical child in the Monte Carlo simulation, each of these three variables will be sampled using a pseudo-random number and the resulting slope will be calculated. Then the hazard standard will be converted from a loading to a concentration using the combination of inputs for that child.

At present, the mechanistic model only describes the floor loading-to-concentration relationship and does not model the accumulation of lead and dust on window sills. The processes governing such accumulation are not as well understood. The model could be extended, however, so that a separate slope could be developed for the window sill conversion.

Each of these two alternative conversion methods has strengths and limitations. The regression equation is based on a nationally-representative dataset with sufficient samples across different housing vintages, outdoor soil concentrations, and indoor paint concentrations. The regression equation has highest reliability for the range of loadings and concentrations in the original dataset, and the hazard standard is expected to fall within that range. The equation is specific to residences, however, and it cannot be easily extended to public and commercial buildings. In addition, the regression equation does not allow any incorporation of variability due to the difference in physical attributes and cleaning patterns among homes. The underlying data show a wide spread across the loading-concentration parameter space, indicating wide house-to-house variability (see Appendix A).

The mechanistic model, on the other hand, allows for extension of the model to public and commercial buildings (which allows consistency in development between this and the parallel approach for commercial and public buildings), provided the physical processes are described adequately and the proper input values can be developed. Because public and commercial buildings tend to be larger, more people come in and out of the buildings daily (and thus introduce more dander to the indoor environment and dilute the indoor dust). In addition, the cleaning patterns are different in public and commercial buildings than in residences; therefore these buildings can be expected to have a very different loading-to-concentration relationship from houses. The model, however, assumes that the indoor environment is well-mixed and contains no concentration gradients; thus, it can be applied to portions of any public or commercial building where this assumption is valid. The mechanistic model also allows for the loading-to-concentration conversion to incorporate house-to-house variability. The mechanistic model is subject to uncertainty, however, because of the relatively simple form of the physical equations and the absence of information about some of the variable inputs. The model has been calibrated against the HUD dataset and then compared to one additional dataset (see Appendix A), and is expected to return reasonable estimates for the national population in the range of the hazard standard. There currently are no data supporting relationships, however, between window sill loadings and concentrations and, unless such slopes are developed, the same slopes as those used for the floor dust would have to be used in developing the window sill hazard standard.

3.4. Characterizing Exposure Variables

3.4.1. Human activity patterns

For the purposes of this approach, an exposure profile describes the amount of time spent by a simulated individual from the population of interest in various microenvironments during a one-year period. The time spent in various microenvironments is provided as an input to subsequent components of the conceptual model presented here to determine the uptake of lead and associated health impacts. A collection of profiles represents a random sample drawn from the target population and it is intended that the statistical properties of the collection of profiles approximate the statistical properties of the target population (in this case, U.S. children under age 6). The simulated individuals spend varying amounts of time in different microenvironments, each with different distributions of lead concentrations, and this approach allows for the characterization of the resulting differences in lead uptake and the associated health impacts.

3.4.1.1. Population of interest

Children under age 6 were selected as the target population for developing residential hazard standards because they are considered most susceptible to adverse health effects from exposure to lead-containing dust in residences. This choice is consistent with studies performed by EPA in support of the benefits analysis for the RRP rule for residential buildings (USEPA 2008b). In order to capture the variability in time spent in residences by children of various ages under age 6, this population is further divided into six, one-year age groups (0-1, 1-2, etc.) for the purposes of estimating exposure concentrations (see Section 3.5).

3.4.1.2. Developing exposure profiles

Exposure profiles will be developed using data from CHAD (USEPA 2009b) for the target population and algorithms from the APEX model. Developed by the EPA's National Exposure Research Laboratory, CHAD contains data collected from several studies designed to capture human activity patterns, and consists of one or more diaries of activities of each participant during the 24-hour period. It is commonly used in exposure assessment and provides required inputs to several EPA exposure models, such as HAPEM, SHEDS, and APEX[1]. Some applications of CHAD data in exposure assessments by EPA include the characterization of inhalation exposures in EPA's National Air Toxics Assessment (NATA) and numerous reviews of the National Ambient Air Quality Standards (NAAQS) for criteria pollutants. Among the various datasets available in CHAD, only the National Human Activity Pattern Study (NHAPS) dataset contains data from a nationally-representative sample. This study, sponsored by the EPA and conducted by the University of Maryland, contains responses from 9,386 participants collected between October 1992 and September 1994. Because it is deemed that NHAPS data may not be sufficient to generate large enough sample of exposure profiles, other studies will also be included to develop activity patterns of simulated individuals. These other studies contain data that is collected from the following specific geographic locations: Cincinnati, Ohio; Baltimore, Maryland; California children study; California adults and youth study; Denver, Colorado; Los Angeles, California; Valdez, Alaska; and Washington, DC.

To generate the activity pattern of a simulated individual for a one-year period, one needs to develop a composite diary from individual 24-hour diaries. A simple approach is to assume that the individual engages in same set of activities and spends same amount of time for an entire period characterized by a CHAD diary. For example, a randomly sampled weekday diary from CHAD can be assumed to be applicable for all weekdays for a simulated individual. While this approach may capture between-person variability in activity patterns in the targeted population, the variation in day-to-day activities of the simulated individual is not modeled. Consequently this approach may result in unrealistically large or small exposure times. Therefore, a probabilistic algorithm that can also capture day-to-day variation in the activity patterns of simulated individuals needs to be applied to develop composite diaries from individual 24-hour diaries.

The Air Pollution Exposure Model (APEX) is a peer-reviewed EPA model that is used to assess inhalation exposure for criteria and toxic air pollutants. The APEX model currently incorporates two stochastic methods to develop composite diaries to evaluate inhalation exposure. The diversity-autocorrelation algorithm assembles multi-day diaries based on reproducing realistic variability in a user-selected key diary variable – the variable that is assumed to have dominant influence on exposure. This algorithm works by first creating diary pools from the CHAD data. A diary pool is a group of CHAD diaries that has a common diary variable that has significant effect on activity patterns. For example, diary pools can be created for each day type (weekday,

[1] HAPEM = Hazardous Air Pollutant Exposure Model; SHEDS = Stochastic Human Exposure and Dose Simulation Model; APEX = Air Pollutants Exposure Model.

weekend day) and season (summer, non-summer) because it is expected that the activities of target population significantly differ from weekday to weekend and between a summer day and a non-summer day. Once diary pools are created, each diary in the pool is assigned a rank, or "x-score," based on the key activity variable. The composite diary is then assembled based on the x-scores using the longitudinal diary assembly algorithm. This algorithm aims to reproduce the user-supplied statistics ***D*** and ***A.*** The ***D*** statistic quantifies the relative importance of within-person and between-person variances in the key activity variable. The ***A*** statistic quantifies the day-to-day autocorrelation, which characterizes the similarity in diaries from day to day. Additional details of this algorithm are presented in the APEX technical support document (USEPA 2008c).

The second algorithm, the Cluster-Markov algorithm, also stochastically generates composite diaries from individual 24-hour period diaries. This approach was developed to better represent variability in activity patterns among simulated individuals. It first groups the CHAD diaries into two or three groups of similar patterns for each of the 30 combinations of day type (summer-weekday, non-summer weekday and weekend), demographic group (males and females), and age groups (0-4, 5-11, 12-17, 18-64, 65+). Next, for each combination of day type and demographic group, category-to-category transition probabilities are defined by the relative frequencies of each second-day category associated with each given first-day category where the same individual was observed for two consecutive days. A composite diary of one year is constructed by first randomly selecting one daily activity pattern from each of the CHAD categories to represent that particular day type and demographic group. Finally, a sequence of daily activities for a one-year period is generated as a one-stage Markov chain process using the category-to-category transition probabilities.

To generate a sufficiently large number of profiles (on the order of tens of thousands), this approach will apply both of the above algorithms and evaluate them for their statistical properties. The algorithm that most adequately represents both the within-person and between-person variability will ultimately be applied to characterize the human activity patterns.

3.4.1.3. Defining microenvironments of interest

While the time spent by children under age 6 in residential buildings is of primary interest, their time spent in other microenvironments also contributes to overall lead uptake and therefore must be characterized. In this approach, time spent by children in the following microenvironments is estimated from CHAD data:

- Residences;
- Child-occupied facilities (COF);
- Outdoors;
- Traveling; and
- Public and commercial building

It is assumed that the time spent in public and commercial buildings includes any time spent in an indoor building environment that is not a residential building or a child-occupied facility, and is estimated from CHAD data by aggregating several location categories. Table 3-2 shows average, median, and 95th percentiles of times spent in these microenvironments from the CHAD data for the six children's age groups considered. Note that the CHAD data contain over 100 location descriptions. For this approach, these locations were aggregated into the five categories mentioned above. For example, the time spent traveling includes general travel, motorized travel, travel by walking, and waiting for bus, train, or other vehicle. Similarly, time spent in other building includes time spent in public buildings (e.g., libraries, museums), hospitals, and commercial buildings (e.g., grocery stores, restaurants).

Table 3-2. Children's Time Spent in Selected Microenvironments, by Age

Age	Residence	COF	Outdoor	Travel	Public/Commercial Buildings
Average time spent (Hours)					
0 - 1	21.32	0.45	0.51	0.81	0.81
1 - 2	20.81	0.53	1.00	0.82	0.76
2 - 3	19.96	0.73	1.4	0.95	0.84
3 - 4	19.56	1.01	1.44	0.96	0.94
4 - 5	18.96	1.38	1.66	0.92	0.99
5 - 6	18.15	2.17	1.73	1.03	0.84
Median time spent (Hours)					
0 - 1	22.00	0	0	0.67	0
1 - 2	21.42	0	0.42	0.58	0
2 - 3	20.50	0	0.67	0.67	0
3 - 4	20.00	0	0.83	0.75	0
4 - 5	19.25	0	1.00	0.75	0
5 - 6	18.17	0	1.00	0.75	0
95th percentile of time spent (Hours)					
0 - 1	24.00	2.71	2.50	2.42	3.91
1 - 2	24.00	6.16	3.84	2.66	3.50
2 - 3	24.00	7.83	5.25	2.83	3.41
3 - 4	24.00	8.34	5.00	2.92	4.00
4 - 5	24.00	8.75	5.68	2.41	3.96
5 - 6	23.50	8.83	5.76	2.84	3.75

3.4.2. Other exposure parameters

Exposure characteristics other than the time spent in each microenvironment also affect the overall exposure of a child to lead. These characteristics or variables include the ingestion rate of dust and soil, the intake rate of lead in the diet, the intake rate of lead in water, the ventilation rate, the lead inhalation and ingestion absorption rates, and the maternal blood lead when the child is born. In order to account for inter-individual variability in exposure in the population, those exposure variables expected to have the highest sensitivity and to vary the most strongly will be sampled from distributions. These include the ingestion of soil and dust by age group, background water lead intake, and background diet lead intake. Distributions for the ingestion of soil and dust will be generated from information in the Child-Specific Exposure Factors Handbook (USEPA 2008a). To estimate the distributions of dietary and water intake of lead, the LifeLine Model (The LifeLine Group 2008) will be used to estimate a distribution of intakes across the population by age. The ventilation rate and maternal blood lead will not be sampled, but central tendency estimates will be taken in order to conserve computational resources; inhalation exposures are not anticipated to contribute in large measure to total lead exposure compared to soil and dust ingestion (USEPA, 2006) and the ventilation rate is not anticipated to be a sensitive variable. In addition, given the elimination rate of lead in children, maternal blood lead has only a minor impact on a child's blood lead levels beyond the age of six months with subsequent blood lead levels determined primarily by environmental exposures. For the absorption fractions, these variables may be sensitive in describing the child's overall response to lead exposure, but information in the literature is currently insufficient to derive distributions, so central tendency values will be used.

The sampled values for each variable differ across the different ages. To account for the potential correlations across ages, these variables will be sampled from age-specific distributions to ensure the same percentiles are used for each age. For example, if a child has 90th percentile ingestion of soil and dust at age 1, they will also have 90th percentile ingestion of dust at age 5, and the actual ingestion values will be taken from the separate distributions for each age.

3.5. Estimating Exposure Concentrations

For each hypothetical child, the Monte Carlo sampling provides dust, soil, and air concentrations of lead for each relevant microenvironment. The concentrations in each microenvironment must then be combined to provide overall air, soil, and dust concentrations for input into the blood lead model. First, the floor and window sill dust concentrations in each microenvironment are combined according to the equation:

$$dust = floor \times frac_{floor,t} + sill \times frac_{sill,t}$$

where:

$dust$	= the average dust exposure concentration in that microenvironment
$floor$	= the concentration of lead in dust on the floor
$frac_{floor,t}$	= fraction of dust exposure arising from floor dust for age range t
$sill$	= the concentration of lead in dust on the window sill
$frac_{sill,t}$	= fraction of dust exposure arising from sill dust for age range t

The $frac_{floor,t}$ variable will be adjusted for each age to account for expected differences between infants, toddlers, preschoolers, and kindergartners. Then, the concentrations for air, soil, and dust across microenvironments will be combined using the fraction of the time spent in each microenvironment for the specific age. The following equation will be used:

$$concen_{\exp,t} = \frac{\sum_{i=1}^{n}(f_{i,t} \times concen_i)}{\sum_{i=1}^{n} f_{i,t}}$$

Where:

$concen_{exp,t}$	=	the exposure concentration for age range t
$f_{i,t}$	=	fraction of time spent in each microenvironment for age range t
$concen_i$	=	the concentration in each microenvironment
n	=	the number of microenvironments in which exposure to the media occurs

In the case of air concentrations, the child is assumed to be exposed to air concentrations in all microenvironments. The child is assumed only to be exposed to dust, however, when indoors (either in the home or outside the home) but not when outdoors or in a vehicle. Similarly, the soil concentrations are only combined using the fractions of time in an outdoor microenvironment. A separate blood lead model input variable accounts for the total ingestion of dust and soil mass and the fraction of total dust+soil ingestion that arises from soil. Thus, provided that the dust and soil concentrations represent the average concentrations to the hypothetical child is expected to be exposed as a result of their activity pattern, the approach assumptions are compatible with the blood lead modeling assumptions.

4. Estimation of Blood Lead Levels

4.1. Overview of Blood Lead Models for Children

A number of different approaches are available to estimate children's blood lead levels in response to defined exposure scenarios (USEPA 2006). Approaches that have been implemented include explicit pharmacokinetic models (where the movement of lead is simulated through compartments with defined volumes and perfusion rates), biokinetic models (where lead moves from compartment to compartment based on first-order rate constants), and empirical models that predict blood lead as a simple regression-like function of steady-state exposure concentrations. In addition to these general-purpose models that take media concentrations or exposures as their inputs, there have been several studies (Rabinowitz et al. 1985, Lanphear 2007) where the impacts of residential renovation activities on blood lead levels have been estimated directly for specific populations of children.

Among the available models, EPA's IEUBK model (USEPA 2010a) is by far the most thoroughly tested and frequently used for assessment of the impacts of exposures in air, soil, house dust, diet and water on children's blood lead concentrations. The IEUBK model was originally developed by EPA's Office of Air Quality Planning and Standards (OAQPS) to support analyses of air quality standards starting in 1985. The model implements a biokinetic model developed by Harley and Kneip (1985) that predicts blood lead levels in children 0-7 years old in response to specified lead exposures. In 1991, responsibility for further development of the IEUBK model was given to the Technical Review Workgroup (TRW), composed of representatives from several EPA program and regional offices. The model was released to the public in 1991 and has been updated continuously since then without basic changes to the model structure, although recommended default exposure factor and environmental concentration values have changed as new data have become available.

The EPA All Ages Lead Model (AALM), now intermittently under development, aims to extend beyond IEUBK's capabilities to model external Pb exposure impacts (including over many years) on internal Pb distribution not only in young children, but also in older children, adolescents, young adults, and other adults well into older years (up to 90 years of age) (USEPA 2005). The AALM essentially uses adaptations of the IEUBK exposure module features, coupled with adaptations of IEUBK biokinetics components (for young children) and of the Leggett model's biokinetics components (for older children and adults). The AALM has not yet undergone sufficient development and validation for it to be recommended for general risk assessment use.

EPA's Clean Air Science Advisory Committee (CASAC) reviewed the use of the IEUBK in support of the 1990 revisions to the National Ambient Air Quality Standard (NAAQS) for lead, and the structure and parameter values in the model have also been reviewed by the Indoor Air Quality and Total Exposure Committee of the Science Advisory Board (SAB). The IEUBK has been subject to external peer review, its performance has been tested against a number of large data sets, and its predictions have been compared to competing pharmacokinetic and biokinetic models (NIEHS 1998, USEPA 2006). The IEUBK was the primary blood lead assessment model used in EPA's risk assessment supporting the lead NAAQS revision (USEPA 2007).

The most plausible alternatives to the IEUBK include the "Leggett" biokinetic model (Leggett 1993) and the pharmacodynamic model developed by O'Flaherty et al. (1993, 1995). The Leggett model was developed with support from the International Agency for Radiological

Protection (ICRP) to support risk assessment for radionuclides of lead and related elements. The model is technically sophisticated, simulating the transfer of lead among 15 compartments in the body, based on a large body of age-specific biokinetic data on lead and other metals. In addition, the default time step for biokinetic simulation is one day instead of the minimum one-month time step used in the IEUBK model, which suggests that the Leggett model might be better suited to modeling the impacts of short-term exposures, such as those in the RRP rule (USEAP 2008b). Despite these potential advantages, the Leggett model has not undergone the same degree of testing against environmental data sets as has the IEUBK. In addition, the Leggett model does not include a detailed exposure model like the IEUBK;and pathway-specific daily intakes must be specified by the user. Detailed comparisons of the IEUBK and Leggett model results indicate that, for plausible exposure scenarios and absorption fraction values, the Leggett model tends to predict higher children's lead uptake and blood lead levels than the IEUBK for similar exposures (USEPA 2006). One important feature of the Leggett model not shared by the IEUBK is that it has the capability to model blood lead overall from birth through adulthood.

The O'Flaherty pharmacodynamic model (O'Flaherty et al. 1993, 1995) is likewise more complex and technically sophisticated in some ways than the IEUBK model. As noted above, it is a truly pharmacodynamic model with lead transfer modeled between compartments with defined age-specific volumes and perfusion rates. In addition, the O'Flaherty model explicitly models the age-related changes in bone growth and deposition/depuration processes. Like the Leggett model, however, the O'Flaherty et al. model has not been subject to the same degree of calibration and testing against human data sets (particularly children) as has the IEUBK. As will be discussed below, in comparison studies, the O'Flaherty et al. and Leggett models tend to give similar blood lead predictions for defined adult exposure scenarios.

Empirical (regression-type) blood lead models based on environmental concentrations were not considered for use in this analysis because the available models (Lanphear et al. 1998b, Schwartz et al. 1998, USEPA 1998) predict steady-state blood lead levels in adults or children assumed to be facing constant exposures from soil, dust, and paint. They are thus poorly suited to estimating the impacts of variable exposures arising from renovation activities. Two studies were also identified (Rabinowitz et al. 1985, Lanphear et al. 2007) that directly estimated the potential impacts of residential renovation on children's blood lead levels. While these studies provide helpful support for the current analysis, neither is suited for exposure-response analysis since the number of exposed subjects is small in both studies and both were conducted in older urban neighborhoods where renovation hazards may not be typical of those in the rest of the U.S. The study by Rabito et al. (2007) was likewise limited to estimating the blood lead impacts of demolition activities in a high-lead area.

4.2. Specific Blood Lead Model: IEUBK

Based on the evaluation described above, the IEUBK was selected for modeling blood lead concentrations for children under 6 years of age in the residential exposure scenario. The IEUBK model is a multicompartmental pharmacokinetics model that, in the default mode, provides estimates of long-term (annual average) blood lead levels in children (birth to 7 years). Used in batch mode, the IEUBK model can provide estimates of blood lead concentrations over shorter time intervals; run in batch mode, temporal resolution of one month can be achieved. That is, input variables can be specified and blood lead outputs can be obtained for each month of exposure. The exposure module simulates intake of lead for six exposure media: air, diet (excluding drinking water), drinking water, outdoor soil/dust, indoor dust, and other. Input variables, including absorption fraction and inhalation rate, water intake, dietary intakes of specific food classes, and outdoor soil/dust and indoor dust ingestion rates, are user-specified. Age-specific lead inhalation uptakes are estimated for exposure to outdoor and indoor air, based on age-dependent estimates of time spent indoors and outdoors, estimates of indoor and outdoor air lead concentrations, and age-dependent inhalation rates. Additionally, a respiratory tract adsorption fraction is used to account for both deposition of inhaled lead in the respiratory tract and absorption of deposited lead from either the respiratory tract or from the gastrointestinal (GI) tract. The model also contains an option for calculating indoor dust lead concentrations based on an empirical relationship among air, outdoor soil/dust, and indoor dust lead levels. Ingestion uptake is calculated using absorption fractions that are specific to the ingested medium (diet, drinking water, outdoor soil/dust, or indoor dust).

Under the default option, total gastrointestinal (GI) lead uptake is modeled as being composed of a saturable and an unsaturable component using the IEUBK default parameters describing the relative importance of these two components as a function of total lead intake. The user may change the model inputs describing the saturable pathway, or turn it off completely. The outputs of the uptake module are estimates of the masses of lead absorbed into the body over time as a function of concentrations in the various exposure media.

In the biokinetic module of the IEUBK model, absorbed lead (from ingestion and inhalation) is assumed to appear immediately in the plasma-extracellular fluid (ECF) compartment. The plasma-ECF compartment constitutes the central compartment in the biokinetic model from which exchange to all other compartments occurs. Trabecular and cortical bone (which are not directly coupled in the IEUBK model) constitute the main long-term storage compartments, with the estimated turnover in other compartments being more rapid. The binding capacity of the red blood cell (RBC) compartment is modeled as being saturable, simulating the limited capacity of aminolevulinate dehydratase (ALAD) and other lead-binding proteins. Lead excretion occurs through a urine pathway (distinct from the kidney compartment). Hepatobiliary secretion is coupled with the liver compartment, with a minor component of excretion from “other soft tissues” (i.e., skin, hair, and nails). The sole output from the IEUBK model is blood lead concentrations for each exposure period; the model does not support the estimation of bone accumulation.

5. Application of the Approach for Residences

Sections 2 through 4 describe the methods used for calculating a child's blood lead concentration distribution by specifying lead dust loadings for the floor and window sill candidate hazard standards and simulating numerous hypothetical individuals, each with different sampled behaviors and environmental media concentrations. The purpose of this model, however, is to calculate the floor and window sill dust lead loadings corresponding to the specific target blood lead levels of 1, 2.5, and 5 µg/dL, or solving for the input of the model with a known output. This section explains the methodology used for calculating dust lead loadings for the candidate hazard standards which result in a target blood lead level.

As described in Section 3, media concentrations and some exposure variables will be sampled probabilistically for all microenvironments except for the set of residential candidate hazard standards (floor and window sill) for each realization. Therefore, each realization will result in a different blood lead concentration, as each sampling will likely have unique set of media concentrations. The same distributions will be used for thousands of unique realizations to generate a distribution of blood lead concentrations associated with each set of candidate hazard standards.

Because the relationship between hazard standards and the various contributions to blood lead concentration does not exist as an equation in closed form, selecting a set of candidate hazard standards that result in a target blood lead concentration consists of two steps:

1. Create a response surface to correlate candidate dust and window sill lead dust loading levels with blood lead levels. The response surface will be constructed by running many iterations with different target loading levels, with a limited number of realizations for each iteration, to generate rough approximations of the corresponding blood lead levels.

2. Using this response surface, predict the target loading that corresponds to a prespecified point on the blood lead concentration distribution[2], and run the model to confirm/deny this prediction. Repeat iteratively until the loading value corresponding with the prespecified point has been precisely determined. This step will involve running fewer iterations with a much higher number of realizations, thus creating highly precise relationships between target loadings and blood-lead levels.

5.1. Creating the Target Loading-to-Blood -Lead Response Surface

Because multiple distributions are sampled for each realization, the resulting distributions of blood lead levels may have a wide range. Therefore, many realizations may need to be simulated in order for the blood lead distribution to become stable (i.e., adequately represent the underlying inputs). To minimize the number of iterations required to identify the candidate hazard standards corresponding to the prespecified blood lead concentration distribution point, a response surface will be created for a range of candidate hazard standards that will provide an educated guess as to what loading will correspond to that percentile for a particular target blood lead level. Because the response surface will be used only to provide an indication of where to estimate

[2] Multiple realizations create distributions of possible values associated with each hypothetical child exposed at a candidate hazard standard. The Xth percentile of each distribution will be selected to permit a simulation-based one-to-one function to be constructed from the surface.

final candidate loadings, fewer realizations can be conducted with each iteration to reduce calculation time.

5.2. Estimating the Candidate Hazard Standard Using the Response Surface

After generating a response surface for range of candidate loadings, a rough estimate of the relationship between candidate loadings and blood lead levels will be known. Using this relationship, a set of candidate loadings can be estimated to correspond with a target blood lead level, and the model is run to determine if the target blood lead level is reached with sufficient precision. Because this analysis is composed of a large number of sampled distributions (Table 5-1), it is suspected that thousands of realizations will be required to reach a stable blood lead level distribution. Stability of the distribution will be assessed using statistical methods roughly comparing variability of the distribution to its median, with variability measures generated by such techniques as the boot-strap method[3].

Table 5-1. Key Input Variables or Variable Groups Sampled in the Residences Model

Group	Sampling independent or correlated?	Variable or Variable Group[a]	Sampling Notes
Candidate hazard standards	Correlated	Dust lead loading, floor, residence	Fixed with each iteration
		Dust lead loading, sill, residence	Fixed with each iteration
Exposure location	Independent	Time spent in each environment	Sampled, resampled annually
Exposure	Independent	Ingestion of lead in drinking water	Sampled, resampled annually
	Independent	Ingestion of lead in diet	Sampled, resampled annually
	Independent	Daily ingestion of dust and soil	Fixed, changes annually
	Independent	Ventilation rate	Fixed, changes annually
	Independent	Lung absorption efficiency	Fixed
Lead loadings/ concentrations in environmental media	Correlated	Dust lead loading, floor, all other areas	Sampled, once per realization
		Dust lead loading, sill, all other areas	Sampled, once per realization
	Independent	Soil lead concentration, outdoors	Sampled, once per realization
	Independent	Air lead concentration, indoors	Sampled, once per realization
	Independent	Air lead concentration, outdoors	Sampled, once per realization

[a] Variables mentioned above may represent multiple distributions, and therefore the number of sampled distributions will actually be greater than what is presented above. In addition, if additional or better input data are found, additional variables mentioned above may be sampled as well.

5.3. Sensitivity Analysis

To better understand each variable's impact on the candidate hazard standards identified, a sensitivity analysis will be conducted on each variable. This sensitivity analysis will provide a better understanding of which variables are most influential to the model, and therefore which variables are most influential in determining the candidate hazard levels. This analysis will use methods consistent with considerations in the Agency intended to conform to current best practice.

[3] The simulations will be run until the standard error of the 90^{th} percentile value of the output blood lead distribution is estimated to be less than 10 per cent of its median.

All sensitivity analyses will be conducted in deterministic mode. Deterministic mode is defined using a single value for each variable (i.e., no sampling will occur). In deterministic mode, each unique group of input variables will have one unique output value. Because no sampling will occur, results will not be impacted by the convergence of output distributions.

Elasticity will be used to determine the impact of each input variable. Elasticity is defined as the percent change in a model output value (i.e., blood-lead level) that results from a fixed percent change in a model input variable value with all other variable values held to a constant baseline value. Baseline case is defined as the central tendency values for all variables in the model. By modifying each variable by the same percent change, elasticicity can be compared across variables to better understand to which variables the model is most/least sensitive.

$$Elasticity = \frac{\frac{y^1 - y^0}{y^0}}{\frac{x^1 - x^0}{x^0}}$$

where:

y^1 = blood lead level, sensitivity case

y^o = blood lead level, baseline case

x^1 = property value, sensitivity case

x^o = model input property value, baseline case

An elasticity of 1 means that a percent change in an input value is linearly related to a percent change in the output value. An elasticity of 0 means that changing the input value has no effect on the output value. An elasticity in absolute value greater than 1 occurs when a percent change in an input value results in a greater percent change in an output value. An elasticity in absolute value less than 1 occurs when a percent change in an input value results in a smaller percent change in an output value. A negative value for elasticity indicates that the output value varies in the opposite direction to the input value change.

For all characteristics (sampled or fixed), variability in a property can be nonlinear. To address this in the sensitivity analysis, two analyses will be conducted: a local analysis (representing small changes in a parameter) and a global analysis (for larger changes). For the local analysis, each parameter in the model will be varied by ± 5% from the central tendency; for the global analysis, each parameter will be varied by ± 50% from the central tendency. If the elasticity of a parameter is different between the local and global analysis, this indicates that this parameter has a nonlinear relationship to blood lead.

Because the model will sample media concentrations from known distributions, additional information is known about the range of possible values from these distributions. Therefore, the sensitivity score will be calculated for parameters which are sampled from a distribution. The sensitivity score is calculated by:

$$Sensitivity\ Score = Elasticity * \frac{\sigma_x}{\mu_x}$$

Where:

σ_x = standard deviation/geometric standard deviation of input distribution

μ_x = mean/geometric mean of input distribution

6. Data Needs

The quality of the results generated using the approach described in this document relies heavily on reliable input data. Among the most important data needs are:

- Media concentrations for residences;
- Media concentrations for public and commercial buildings;
- Media concentrations for near-roadway areas;
- Media concentrations for outdoors;
- Relationship between window sill and floor dust lead exposures;
- Inputs to the blood lead models; and
- Inputs to the mechanistic dust lead loading-to-concentration model.

This section discusses the data identified thus far for each of the types of data, with the exception of the inputs to the mechanistic loading-to-concentration model and those for the floor-dust-to-sill-dust correlation, which are discussed in Appendix A.

6.1.1. Media concentrations for residences

As listed in Table 3-1, air lead concentration distributions are needed in residences. The dust concentrations will be the target hazard standards and will not need to be approximated from literature data. The approach proposes to use the monitoring data of the Air Quality System (AQS) to develop suitable distributions (USEPA 2010b). In the system, each monitor is assigned a monitoring objective code, as shown in Table 6-1. In order to capture the typical exposure concentrations for the national population, data from all monitors with coverage in 2009 and 2010 for the codes 6 (Population Exposure) and G (General/Background) will be pulled. The data will be annually-averaged, and a distribution across the available values will be developed. In order to capture the total lead content, the analysis will focus on lead Total Suspended Particulate (TSP) monitors.

These monitors provide outdoor air concentrations around the country. To generate indoor concentrations, a factor will be applied to the outdoor concentrations to approximate the indoor concentration. Thatcher and Layton (1995) report that Colome et al. (1992) found an average indoor/outdoor ratio of 0.7 in 35 California homes. This is also the average indoor/outdoor ratio predicted by the approach's mechanistic dust model when applied to the HUD data set (USEPA 1995; see Appendix A). Thus, the ambient concentration will be multiplied by 0.7 to convert to an approximate indoor concentration.

Table 6-1. AQS Monitor Objective Codes

Monitor Code	Monitor Objective
0	UNKNOWN
1	UPWIND BACKGROUND
2	MAX PRECURSOR EMISSIONS IMPACT
3	MAX OZONE CONCENTRATION
4	EXTREME DOWNWIND
5	OTHER
6	POPULATION EXPOSURE
7	SOURCE ORIENTED
8	REGIONAL TRANSPORT
9	WELFARE RELATED IMPACTS
G	GENERAL/BACKGROUND
H	HIGHEST CONCENTRATION
I	INVALID CODE TEST

6.1.2. Media concentrations for public and commercial buildings

As specified in Table 3-1, distributions of indoor dust floor loadings, indoor dust window sill loadings, and indoor air concentrations are needed for public and commercial buildings. An extensive internet search was performed to identify studies conducted in public/commercial settings that may be useful in developing loading distributions for different building types. Data for both child-occupied facilities and other commercial buildings where children spend time were separately collected, and distributions for each will be estimated.

For the air concentrations, data may not be available to separately define residential and public and commercial building ambient air concentrations. Thus, the approach will likely use the same ambient concentration as used in residences. A literature search will be conducted to identify typical indoor/outdoor air concentration ratios in public and commercial buildings for use in converting to indoor concentrations.

6.1.3. Media concentrations near roadways

An exposure concentration in air is also required for the “traveling” microenvironment. Attempts will be made to locate air lead concentrations which are typical on and near roadways. Then, the assumption will be made that the “traveling” microenvironment concentration equals the outdoor ambient concentration.

6.1.4. Media concentrations outdoors

For the outdoor microenvironment, the approach requires outdoor soil concentrations. The HUD survey (USEPA 1995) provides soil concentrations at residences. These concentrations will be used to develop residential soil distributions.

For outdoor locations away from the home, available public and commercial soil lead concentrations will be compared to the residential values and a separate distribution will be developed if needed.

6.1.5. The relationship between window sill and floor exposures

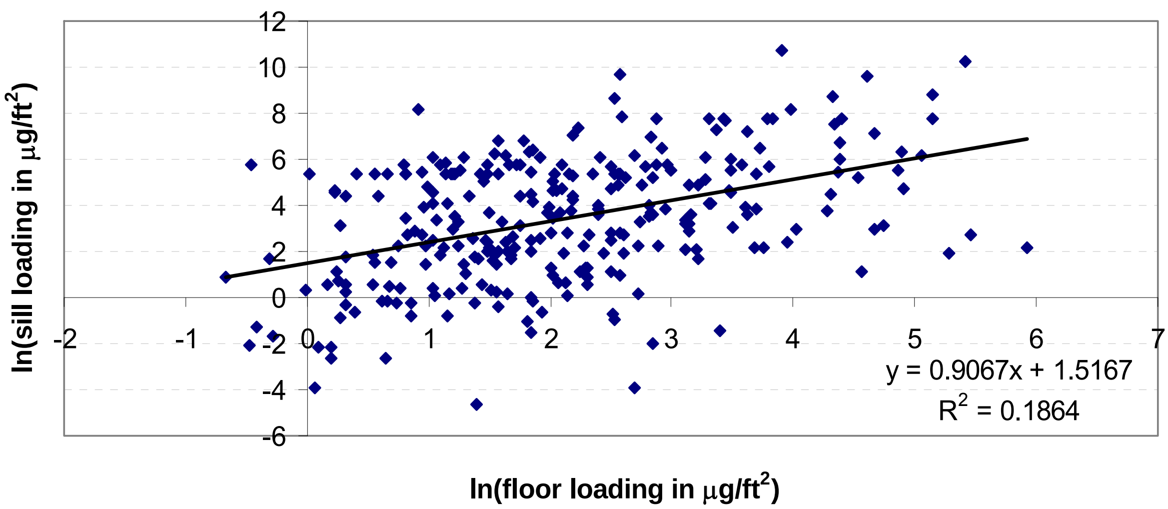
In order to combine the indoor dust concentrations into a single exposure level, the floor and sill levels must be combined according to the approximate relative ingestion of each. The benefits analysis for the LRRP rule (USEPA 2008b) used a weighting strategy based on surface area. This would give approximately 1% weighting to sills and 99% weighting to floors.

A literature search was conducted to determine if any other exposure assessments have made assumptions of the relative contributions of floor and sill. To date, only a single document has been found. The assessment focused on lead and arsenic exposures associated with the presence of indoor paint. It was submitted to the ATSDR and was prepared by the California Department of Health Services (CDC 2002). In the assessment, the assumption was made that sills contribute 1% in infants, 5% in toddlers, 17% in young children, 25% in older children, and 25% in adults. These assumptions appear to represent the authors' professional judgment and do not reflect any measurements that could inform the weighting strategy chosen for this approach. Consequently, the relative floor area assumption will be used.

In addition to combining the floor and sill concentrations into a single aggregate dust concentration, the candidate window sill hazard standard will need to be determined corresponding to each candidate floor hazard standard. Because these two loadings are expected to be correlated in a single building, the approach proposes to develop an empirical relationship to combine them in residences. One potential dataset is the HUD survey data (USEPA 1998). The data from homes constructed before 1980 were used to develop a preliminary relationship between floors and sills for this approach. Figure 6-1 shows the regression model for this dataset; details of this analysis are described in the appendix. The data were natural-log-transformed, since doing so resulted in an apparently higher regression coefficient. The correlation between the variables indicates moderate correlation (r = 0.43). The equation relating the two loadings would then be

$$Sill = 4.56 \times Floor^{0.91}.$$

Figure 6-1. Regression Relationship between Ln(Sill) and Ln(Floor) for the HUD Data

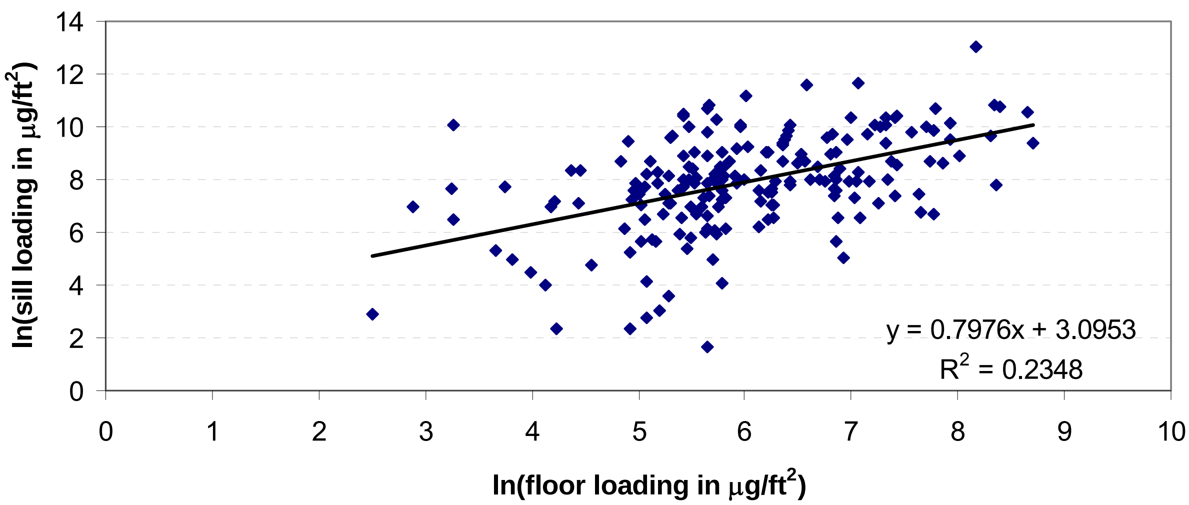


In addition, the Rochester data (Lanphear et al., 1998a) could be used to derive an empirical relationship. As in the HUD data, the natural-log-transformed variables are better correlated than the untransformed variables; the regression is presented in Figure 6-2. In this case, the correlation is slightly higher (r = 0.48) and the equation relating sill to floor loading would be

$$Sill = 22.1 \times Floor^{0.80}.$$

A literature search will be conducted to determine if additional details about the empirical relationship can be found.

Figure 6-2. Regression Relationship between Ln(Sill) and Ln(Floor) for the Rochester Data



6.1.6. Inputs to the blood lead models

The blood lead models require a number of inputs in addition to the air, soil, and dust concentrations. Table 6-2 shows the inputs and the proposed values for each of these inputs. As a starting point, the selected values are the same as those used in the development of the benefits analyis for the lead renovation and repair rule (USEPA 2008b). Several input values were then updated with data from recently published literature. Other values, however, were found to still reflect the best information available. These included the lead absorption fractions and the fraction of ingested soil+dust which is soil.

In 2008, EPA published a new edition of its Child-Specific Exposure Factors Handbook, in which updated values for total indoor/outdoor dust ingestion and ventilation rate were presented (USEPA 2008a). Where ages were expressed as a range in that report, rates for intermediate ages were interpolated using linear trendlines. Mean and 95th percentile values are available for both the dust ingestion and the ventilation rates. For the dust ingestion, the mean and and 95th percentile values will be used to establish a lognormal distribution which will then be sampled as part of the Monte Carlo simulation. For ventilation rates, the mean age-specific values will be used in developing the hazard standards. Because inhalation rates have been found in previous analyses not strongly to affect the predicted blood lead levels in children (USEPA 2006), this variable is not sampled in order to minimize the number of Monte Carlo realizations necessary to resolve the blood lead distribution.

For the dietary and water lead intakes, distributions will be generated using the LifeLine ™ Model (The LifeLine Group 2008). This model will predict distributions of water and dietary lead intake for each medium by age group. Because the IEUBK includes both a water consumption term and a water concentration term, the consumption will be set to one liter per day and the intake will be used in place of the concentration.

The IEUBK value for maternal blood lead level has been updated using data from the most recent NHANES survey. These data from 2007 and 2008 (CDC 2009b) reveal that the nationally weighted GM blood lead level among women aged 18 through 45has fallen over the last fifteen years to 0.847 µg/dL.

Table 6-2. Proposed Blood Lead Model Input Values

Group	Parameter	Parameter Name	Parameter Value							Basis/Derivation
			IEUBK Default Age Ranges (Years)							
			0.5 to 1	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7	
Inhalation	Daily ventilation rate (cubic meters [m^3]/day)	Ventilation rate	5.4 (95% 8.1)	8.0 (95% 12.8)	9.5 (95% 15.9)	10.9 (95% 16.2)	10.9 (95% 16.2)	10.9 (95% 16.2)	12.4 (95% 18.7)	EPA Child-Specific Exposure Factors Handbook (USEPA 2008a) with interpolation for intermediate ages
	Absolute inhalation absorption fraction (unitless)	• Lung absorption (IEUBK) • Absolute respiratory absorption fraction (Leggett)	0.42							USEPA (1989) Appendix A
	Indoor air Pb concentration	Indoor air Pb concentration (percentage of outdoor)	100%							These values are taken directly into account when developing the exposure concentrations
	Time spent outdoors	Time spend outdoors (hours/day)	Not used							
Drinking Water Ingestion	Water consumption (L/day)	Water consumption (L/day)	1	1	1	1	1	1	1	These values are set to 1, since the water consumption will be incorporated into the water ingestion estimate used in the next row.
	Water Pb concentration (µg/L)	Pb concentration in drinking water (µg/L)	Distribution to be estimated from the LifeLine model							The LifeLine ™ model will be used to estimate the distribution of lead intake from water. Because the water consumption is set to 1 in the model, the intakes can be entered in place of the lead concentrations.
	Absolute absorption	• Total percent accessible (IEUBK) • Absolute GI	50 % (Single value used across all age ranges)							Assumed similar to dietary absorption (see "Total percent

Table 6-2. Proposed Blood Lead Model Input Values

Group	Parameter	Parameter Name	Parameter Value: IEUBK Default Age Ranges (Years) 0.5 to 1	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7	Basis/Derivation
	(unitless)	absorption fraction (Leggett)								accessible" under Diet below).
Diet	Dietary Pb intake (µg/day)	Dietary Pb intake (µg/day)	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	Distribution to be estimated from the LifeLine model	The LifeLine ™ model will be used to estimate the distribution of dietary intake by age group
Diet	Absolute absorption (unitless)	(1)Total percent accessible (IEUBK) (2) Absolute GI absorption fraction	50%							Alexander et al. (1974) and Ziegler et al. (1978) as cited in USEPA (2006, section 4.2.1)
Outdoor Soil/Dust and Indoor Dust Ingestion	Outdoor soil/dust and indoor dust weighting factor (unitless)	• Outdoor soil/dust and indoor dust ingestion weighting factor (percent outdoor soil/dust) (IEUBK) • Outdoor soil/dust and indoor dust ingestion rates calculated separately using same proportion of outdoor soil/dust ingestion (Leggett)	45 percent							This is the percent of total ingestion that is outdoor soil/dust. Value reflects best judgment and consideration (results published by van Wijnen et al. (1990), as cited in (USEPA 1989). The van Wijnen et al. study examined at tracer studies of ingestion rates for rainy days and non–rainy days. It was assumed that rainy days were associated with all outdoor soil/dust ingestion and non-rainy days were associated with a combination of outdoor soil/dust and indoor dust with the delta representing outdoor soil/dust.

Table 6-2. Proposed Blood Lead Model Input Values

Group	Parameter	Parameter Name	Parameter Value							Basis/Derivation
			IEUBK Default Age Ranges (Years)							
			0.5 to 1	1 to 2	2 to 3	3 to 4	4 to 5	5 to 6	6 to 7	
	Total indoor dust + outdoor soil/dust ingestion (mg/day)	Amount of outdoor soil/dust and indoor dust ingested daily (mg)	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from percentiles	Distribution estimated from the EPA Child-Specific Exposure Factors Handbook (USEPA 2008a), excluding cases of soil-pica and geophagy
	Absolute gastrointestinal absorption (outdoor soil/dust and indoor dust) (unitless)	• Total percent accessible (IEUBK) • Absolute GI absorption fraction (Leggett)	0.30 for both outdoor soil/dust and indoor dust							(USEPA 1989) reflects evidence that Pb in indoor dust and outdoor soil/dust is as accessible as dietary Pb and that indoor dust and outdoor soil/dust ingestion may occur away from mealtimes (resulting in enhanced absorption relative to exposure during meal events).
Other	Maternal PbB (µg/dL)	Maternal PbB concentration at childbirth, µg/dL	0.847							NHANES 2007-2008, national weighted GM of all women aged 18-45 (CDC 2009b)

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Appendix A. Loading to Concentration Conversion Methods

The indoor lead hazard standard prescribes the amount of lead allowed on the surface per unit area (lead loading). The blood lead models, however, cannot accept lead loadings as inputs. Instead, they require the lead concentration, or the amount of lead per mass of dust. Thus, as part of the derivation of the hazard standard, dust loadings must be converted to dust concentrations for input into the blood lead models. Two different estimates have been developed for this approach, based on two different methodologies: 1) a statistical regression model and 2) a mechanistic model. Sections A.1 through A.3 describe these estimates and highlight the strengths and limitations of each. Section A.4 describes the development of the regression used for the relationship between floor lead dust loading and window sill lead dust loading.

A.1 Development of a Regression Equation

The National Survey of Lead-Based Paint in Housing ("HUD Survey Data") was used to develop a loading-to-concentration regression equation for this approach. The data, available in Appendix C-1 in a risk assessment (US EPA, 1998), provide information on wipe sample lead dust loadings, vacuum sample lead dust loadings, and blue nozzle lead concentrations on the floor for over 312 homes in different vintage categories: Pre1940, 1940-1959, 1960-1979, and Post1980. It is anticipated that the wipe samples better capture the total lead present in the home; the vacuum samples are subject to vacuum collection efficiencies. Thus, the wipe loadings were paired with the blue nozzle concentrations at each home to develop the loading-to-concentration statistical relationship. By doing so, the assumption is made that the concentration is roughly uniform across all particles and the particles collected by the blue nozzle device are representative of the true average concentration. In order to focus on the homes containing lead paint, only the data from the older three vintage categories were included. This eliminated 28 data points from the dataset. Some statistics from the reduced dataset are provided in Table A-1. In general, the spread in the data is large and covers loadings up to 375 μg/ft^2 and concentrations up to 50,400 μg/g. The range of considered hazard standards is below the 95th percentile loadings, so the results of the regression are anticipated to apply to the hazard standard in residences.

Table A-1. Statistics from the HUD Survey Data

	Loading (μg/ft^2)	Concentration (μg/g)
Average	20.99	559.08
Min	0.51	0.09
Max	375.00	50400.00
5th percentile	1.25	33.85
25th percentile	3.27	101.75
50th percentile	7.43	201.00
75th percentile	17.38	374.25
95th percentile	96.10	1522.50

From the raw data, each loading and concentration was transformed by taking the natural log. Then, the regression was carried out using the untransformed variables and also the natural-log-transformed variables. Table A-2 shows the results of each regression.

Table A-2. Regression Analysis Results

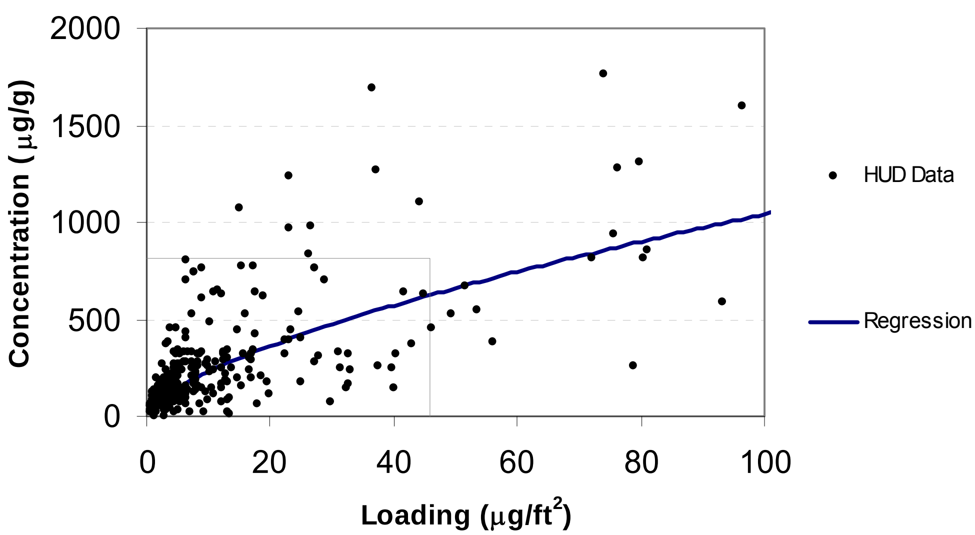
Data	Variable	Coefficient	Standard Error of Coefficient	t-stat	p-value	F-stat, p-level	Adjusted R2
Untransformed	Intercept	159.74	195.86	0.82	0.42	19.88, <0.0000	0.065
	Slope	19.02	4.26	4.46	<0.0000		
Natural-log-transformed	Intercept	3.93	0.10	38.11	<0.0000	246.75, <0.0000	0.465
	Slope	0.6655	0.42	15.71	<0.0000		

The data are positively skewed, and the regression analysis reveals that the log-transformed data provide a regression with a larger adjusted R^2 value. Thus, the log-transformed relationship is chosen, and after accounting for the natural log transformation, the equation relating concentration and loading is:

$$Concen = 50.96 \times Loading^{0.6553}.$$

Figure A-1 below shows the raw data and the regression relationship. The gray line segments define a box at the 90th percentiles in the loading and the concentration.

Figure A-1. HUD Data and the Regression Relationship



A.2 Development of a Mechanistic Dust Model

The mechanistic model is designed to capture the physical transfer of mass from one medium to another under the assumption of mass balance. Previous studies have also built mass balance models of indoor dust. Allott et al. (1994) constructed a mass balance model to estimate the residence time of contaminated soil particles in the indoor environment based on observations in four homes in England contaminated by the Chernobyl incident. Thatcher and Layton (1995) constructed an indoor mass balance model of a home in California to estimate deposition rates, resuspension rates, and infiltration factors. Recognizing the key role of tracked-in soil on indoor dust loadings, Johnson (2008) built the DIRT model simulating the spatial pattern of tracked-in soil for a given total soil mass flux into the home. Layton and Beamer (2009) built a model simulating tracked-in soil and penetration of outdoor air and the subsequent physical processes governing indoor dust loadings. These models cannot be readily applied for developing an approach for the lead hazard standards, however, because they do not include any dust source from lead-containing paint. A new model was constructed for the hazard standard approach and the parameters were optimized against all available data, as described below. Where applicable, the resulting parameters are compared to those found in the above studies to help frame the model in the existing literature. This mechanistic model is deterministic in its underlying nature.

The general form of the mass balance equation for a single compartment of interest is:

$$\frac{d[Mass]}{dt} = Flux\ of\ \ Mass\ In - Flux\ of\ \ Mass\ Out$$

where:

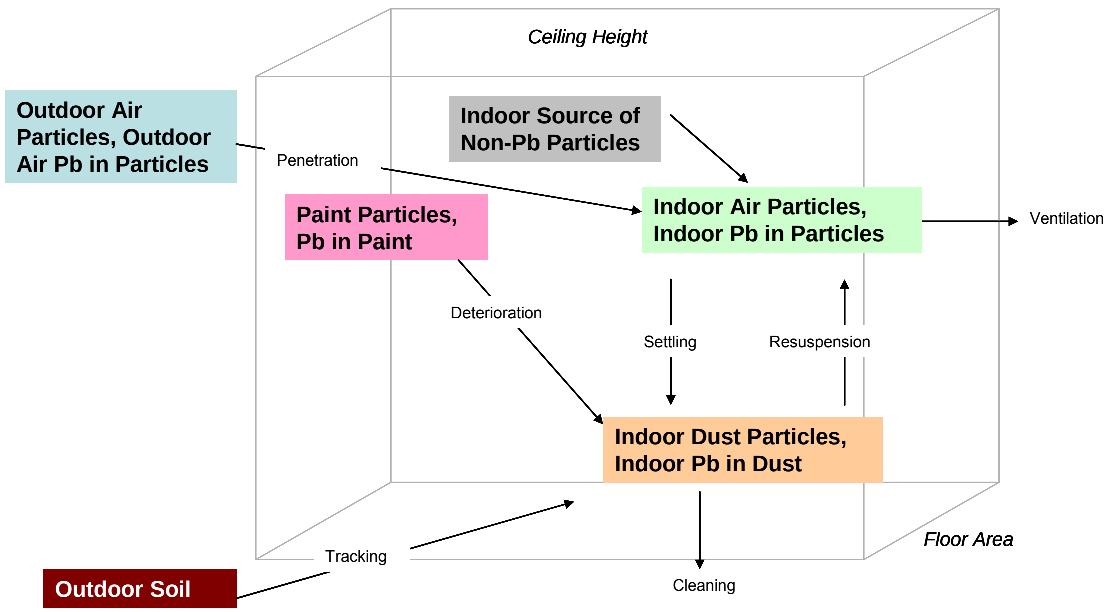
d[Mass]/dt	= change over time of the mass
Flux of Mass In	= flux of mass into the compartment
Flux of Mass Out	= flux of mass out of the compartment

In the dust model, two "compartments" of interest are defined: the indoor air and the floor. Both of these compartments will contain particulates associated with indoor dust, and by parameterizing the processes that govern the flux of mass to and from each compartment, the model can provide an inventory of dust in the air and on the floor through time.

In the above equation, "mass" could refer to either the mass of lead that penetrates the home and settles on the floor in the dust or it could refer to the mass of the dust particles themselves. Because the blood lead model needs inputs of lead dust concentration, the mechanistic model must separately account for both the mass of lead and the mass of dust particulate that accumulates on the floor. Then, by dividing the total lead mass by the total dust mass, the model provides an estimate of the average lead dust concentration. Thus, for each compartment there are two separate equations, one for the lead mass and one for the dust particulate mass.

The dominant sources of lead to the indoor dust are ambient air particles which penetrate the indoor environment and settle on the floor, outdoor soil particles which are tracked into the home, and lead-containing paint which flakes or chips off the walls and settles to the floor. Dust particles have the same sources, although non-lead dust particles are also formed indoors through human activities such as cooking and smoking and by the accumulation of human and pet dander. Figure A-2 shows a schematic of the various lead and particulate mass flux terms used in the mechanistic model to account for all sources and sinks of mass.

Figure A-2. Mechanistic Indoor Dust Model Schematic



For the indoor air compartment, the fluxes for mass include penetration of air and particles from outdoors, ventilation of indoor air back to the outdoor environment, deposition of mass out of the air, resuspension of accumulated mass on the floor back into the air, generation due to indoor sources (where cooking and smoking are thought to dominate these sources), and generation due to the formation of human and pet dander[d]:

$$\frac{dINAIR_{Pb}}{dt} = Penetration\ Flux_{Pb} - Ventilation\ Flux_{Pb} - Deposition\ Flux_{Pb} + Resuspension\ Flux_{Pb} + Indoor\ Sources_{Pb} + Dander\ Sources_{Pb}$$

$$\frac{dINAIR_{Part}}{dt} = Penetration\ Flux_{Part} - Ventilation\ Flux_{Part} - Deposition\ Flux_{Part} + Resuspension\ Flux_{Part} + Indoor\ Sources_{Part} + Dander\ Sources_{Part}$$

where:

[d] The presence of an HVAC system will tend to re-circulate indoor air, passing the air through a filter with each circulation. This system will tend to remove mass from the indoor environment (both in the air and on the floor) and act as a further sink. Because the circulation rate and filtration efficiency of such systems has not been comprehensively described in the literature and because use of such systems changes across the seasons and different geographic regions, removal of mass during recirculation is not included in the mechanistic model.

$dINAIR_{Pb}/dt$ = change in time of the indoor air lead mass
$dINAIR_{Part}/dt$ = change in time of the indoor air particulate mass
Penetration Flux = penetration of air containing particles from outdoors
Ventilation Flux = ventilation of indoor air back to the outdoor environment
Deposition Flux = deposition of mass out of the air
Resuspension Flux = resuspension of accumulated mass on the floor back into the air
Indoor Sources = generation of mass due to indoor sources such as cooking or smoking
Dander Sources = generation of mass due to human and pet dander

In general, each flux is parameterized as either a constant source or as the mass of the "donor" compartment multiplied by the rate (expressed in reciprocal time) of the physical exchange process. In some cases, an efficiency factor is also included to account for any filtration of lead associated with the process. In addition, there is a separate flux term for the lead mass and for the particulate equations. For the *Penetration Flux*,

$$Penetration\ Flux_{Pb} = AER \times P \times PbAIR \times V$$

$$Penetration\ Flux_{Part} = AER \times P \times PartAIR \times V$$

where:

$Penetration\ Flux_{Pb}$ = penetration of air lead from outdoors (µg/h)
$Penetration\ Flux_{Part}$ = penetration of air particles from outdoors (g/h)
AER = air exchange rate (h^{-1})
P = penetration efficiency (unitless)
$PbAIR$ = concentration of lead in ambient air ($\mu g/m^3$)
$PartAIR$ = concentration of particles in ambient air (g/m^3)
V = volume of the house (m^3)

Because the air exchange rate (*AER*) specifies the number of times the indoor air is replaced by outdoor air in a given hour, it represents both the rate of penetration in and ventilation out. The ventilation flux out of the house is thus given by:

$$Ventilation\ Flux_{Pb} = AER \times INAIR_{Pb}$$

$$Ventilation\ Flux_{Part} = AER \times INAIR_{Part}$$

where:

$Ventilation\ Flux_{Pb}$ = ventilation of indoor lead in air back to the outdoor environment (µg/h)
$Ventilation\ Flux_{Part}$ = ventilation of indoor particulate in air back to the outdoor environment (g/h)

AER = air exchange rate (h^{-1})
$INAIR_{Pb}$ = indoor mass of lead in air (µg)
$INAIR_{Part}$ = indoor mass of particulate in air (g)

The deposition flux (*Deposition Flux*) is defined as the amount of mass in the air times a deposition rate:

$$Deposition\ Flux_{Pb} = D \times INAIR_{Pb}$$

$$Deposition\ Flux_{Part} = D \times INAIR_{Part}$$

where:

$Deposition\ Flux_{Pb}$ = deposition of lead out of the air (µg/h)
$Deposition\ Flux_{Part}$ = deposition of particulate out of the air (g/h)
D = deposition rate (h^{-1})
$INAIR_{Pb}$ = indoor mass of lead in air (µg)
$INAIR_{Part}$ = indoor mass of particulate in air (g)

For resuspension, the amount of resuspended material depends on the total available mass on the floor multiplied by a resuspension rate:

$$Resuspension\ Flux_{Pb} = R \times FLOOR_{Pb}$$

$$Resuspension\ Flux_{Part} = R \times FLOOR_{Part}$$

where:

$Resuspension\ Flux_{Pb}$ = resuspension of lead out of the air (µg/h)
$Resuspension\ Flux_{Part}$ = deposition of particulate out of the air (g/h)
R = deposition rate (h^{-1})
$FLOOR_{Pb}$ = mass of lead on the floor (µg)
$FLOOR_{Part}$ = mass of particulate on the floor (g)

For the indoor sources of mass, each source is set equal to a constant rate:

$$IndoorSources_{Pb} = 0$$

$$DanderSources_{Pb} = 0$$

$$IndoorSources_{Part} = CookingRate_{Part} + SmokingRate_{Part}$$

$$DanderSources_{Part} = DanderRate_{Part}$$

where:

$IndoorSources_{Pb}$	= source of lead due to cooking and smoking (µg/h); assumed to be zero.
$DanderSources_{Pb}$	= source of lead due to formation of dander (µg/h); assumed to be zero.
$IndoorSources_{Part}$	= source of particulate due to cooking and smoking (g/h)
$CookingRate_{Part}$	= rate of generation of particulate mass due to cooking (g/h)
$SmokingRate_{Part}$	= rate of generation of particulate mass due to smoking (g/h)
$DanderSources_{Part}$	= source of particulate due to formation of dander (g/h)
$DanderRate_{Part}$	= rate of generation of particulate mass due to dander (g/h).

So, using the penetration, ventilation, deposition fluxes, and indoor source terms, the equation for the change in time of the indoor air lead mass is:

$$\frac{dINAIR_{Pb}}{dt} = AER \times P \times PbAIR \times V - AER \times INAIR_{Pb} - D \times INAIR_{Pb} + R \times FLOOR_{Pb}$$

$$\frac{dINAIR_{Part}}{dt} = AER \times P \times PartAIR \times V - AER \times INAIR_{Part} - D \times INAIR_{Part} + R \times FLOOR_{Part} + CookingRate_{Part} + SmokingRate_{Part} + DanderRate_{Part}$$

where:

$dINAIR_{Pb}/dt$	= change in time of the indoor air lead mass (µg/h)
$dINAIR_{Part}/dt$	= change in time of the indoor air particulate mass (g/h)
$INAIPR_{Pb}$	= indoor mass of lead in air (µg)
$INAIPR_{Part}$	= indoor mass of particulate in air (µg)
$FLOOR_{Pb}$	= mass of lead on the floor (µg)
$FLOOR_{Part}$	= mass of particulate on the floor (g)
$PbAIR$	= concentration of lead in ambient air (µg/m^3)
$PartAIR$	= concentration of particulate in ambient air (g/m^3)
AER	= air exchange rate (hour^1)
P	= penetration efficiency (unitless)
V	= volume of the house (m^3)
D	= deposition rate (h^{-1})
R	= resuspension rate (h^{-1})

$CookingRate_{Part}$ = rate of generation of particulate mass due to cooking (g/h)

$SmokingRate_{Part}$ = rate of generation of particulate mass due to smoking (g/h)

$DanderRate_{Part}$ = rate of generation of particulate mass due to dander (g/h).

For the indoor floor dust compartment (*FLOOR*), the fluxes include deposition of lead from the air onto the floor, resuspension of lead from the floor into the air, flaking of paint from the walls, tracking of lead from outdoor soil, and removal of lead due to routine cleaning:

$$\frac{dFLOOR_{Pb}}{dt} = Deposition\ Flux_{Pb} - Resuspension\ Flux_{Pb} + PaintFlux_{Pb} + TrackingFlux_{Pb} - Cleaning\ Flux_{Pb} \quad \text{(Equation 1A)}$$

$$\frac{dFLOOR_{Part}}{dt} = Deposition\ Flux_{Part} - Resuspension\ Flux_{Part} + PaintFlux_{Part} + TrackingFlux_{Part} - Cleaning\ Flux_{Part} \quad \text{(Equation 1B)}$$

where:

dFLOOR/dt = change in time of the indoor floor mass

Deposition Flux = deposition of mass out of the air onto the floor

Resuspension Flux = resuspension of mass from the floor into the air

Paint Flux = flaking of lead-containing paint onto the floor

Tracking Flux = tracking of soil inside from outdoors

Cleaning Flux = removal of lead due to routine cleaning.

The deposition flux (*Deposition Flux*) and resuspension flux (*ResuspensionFlux*) retain the same form as in the *INAIR* equations. The paint flux is parameterized using a paint chipping fraction, a wall area expressed as the wall loading multiplied by the house volume, and lead paint concentration for the lead mass and the same paint chipping fraction and wall area with a coverage density for the particulate mass. The chipping fraction is explicitly assumed to account for the mass that falls on the floor rather than any mass that lands on window sills or other surfaces:

$$Paint\ Flux_{Pb} = PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv$$
$$Paint\ Flux_{Part} = CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv$$

where:

$PaintFlux_{Pb}$ = generation of lead in air due to deterioration of lead-containing paint (µg/h)

$PaintFlux_{Part}$ = generation of particulate in air due to deterioration of lead-containing paint (µg/h)

PbPaintConcen = lead concentration in the paint (mg/cm^2)
ChipFraction = fraction of total wall area which flakes from the walls per year (year^{-1})
V = volume of the home (m^3)
WallLoading = area of wall space per unit volume of the home (m^2/m^3)
CoverageDens = the coverage density of paint on the wall (g/m^2)
UnitConv = unit conversion necessary to make units consistent (1 year/8760 h).

The tracking flux (TrackingFlux) is parameterized specifically according to the limited data available about the process. Von Lindern et al. (2003) measured the amount of particulate deposited on front mats in 276 houses in two locations near the Bunker Hill Superfund Site. The lead levels reported in the paper are expected to be high-end and are not expected to represent general population exposures. This approach assumes, however, that the rate of accumulation of dust (as opposed to the lead in the dust) on doormats is not strongly affected by the location and can be used to represent a national population of homes. In addition, Thatcher and Layton (1995) measured the difference between particulate accumulation in tracked and untracked areas in the home as well as the amount on the front mat. From these two data sources, it is possible to estimate a distribution of mat particulate accumulation rates as well as the fraction of material that remains on the mat compared to being tracked into the home. For this reason, the tracking is parameterized as:

$$Tracking\ Flux_{Pb} = PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac}$$

$$Tracking\ Flux_{Part} = TrackingRate \times \frac{(1 - MatFrac)}{MatFrac}$$

where:

TrackingFlux$_{Pb}$ = accumulation of tracked-in lead on the floor (µg/h)
TrackingFlux$_{Part}$ = accumulation of tracked-in particulate on the floor (g/h)
PbSoilConcen = concentration of lead in the tracked-in soil (µg/g)
TrackingRate = rate at which particulate is deposited on front mats (g/h)
MatFrac = fraction of total tracked material which is deposited on the front mat (as opposed to the remainder of the house) (unitless).

The cleaning flux (*Cleaning Flux*) is parameterized assuming a cleaning efficiency (*CE*) and cleaning frequency (*CF*) and multiplying these by the mass on the floor (*FLOOR*):

$$Cleaning\ Flux_{Pb} = CE \times CF \times FLOOR_{Pb}$$

$$Cleaning\ Flux_{Part} = CE \times CF \times FLOOR_{Part}$$

where:

Cleaning Flux$_{Pb}$ = removal of lead due to routine cleaning (µg/h)

$Cleaning\ Flux_{Part}$ = removal of particulate due to routine cleaning (g/h)
CE = cleaning efficiency (unitless)
CF = cleaning frequency (cleanings/h)
$FLOOR_{Pb}$ = mass of lead on the floor (μg)
$FLOOR_{Part}$ = mass of particulate on the floor (g).

In the above parameterization, the lead and particulate appear to be cleaned separately, although they are actually present on the same physical particles; by applying the same cleaning equation to both the mass of lead and the mass of particulate, the assumption is made that cleaning occurs over the whole floor and the concentration of lead on the particles is roughly uniform across all particles on the floor.

Combining the floor fluxes then gives:

$$\frac{dFLOOR_{Pb}}{dt} = D \times INAIR_{Pb} - R \times FLOOR_{Pb} + PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv + PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} - CE \times CF \times FLOOR_{Pb}$$

(Equation 2A)

$$\frac{dFLOOR_{Part}}{dt} = D \times INAIR_{Part} - R \times FLOOR_{Part} + PbCoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv + TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} - CE \times CF \times FLOOR_{Part}$$

(Equation 2B)

where:

$dFLOOR_{Pb}/dt$ = change in time of the indoor floor lead mass (μg/h)
$dFLOOR_{Part}/dt$ = change in time of the indoor floor particulate mass (g/h)
$INAIPR_{Pb}$ = indoor mass of lead in air (μg)
$INAIPR_{Part}$ = indoor mass of particulate in air (μg)
$FLOOR_{Pb}$ = mass of lead on the floor (μg)
$FLOOR_{Part}$ = mass of particulate on the floor (g)
D = deposition rate (h^{-1})
R = resuspension rate (h^{-1})
$PbPaintConcen$ = lead concentration in the paint (mg/cm^2)
$ChipFraction$ = fraction of total wall area which flakes from the walls per year ($year^{-1}$)
V = volume of the home (m^3)

WallLoading = area of wall space per unit volume of the home (m^2/m^3)
CoverageDens = the coverage density of paint on the wall (g/m^2)
UnitConv = unit conversion necessary to make units consistent 1 year/8760 h)
PbSoilConcen = concentration of lead in the tracked-in soil (µg/g)
TrackingRate = rate at which particulate is deposited on front mats (g/h)
MatFrac = fraction of total tracked material which is deposited on the front mat (as opposed to the remainder of the house) (unitless)
CE = cleaning efficiency (unitless)
CF = cleaning frequency (cleanings/h).

The above equations can be converted to difference equations by assuming a discrete time step and the model can be integrated forward in time to describe the lead and particulate accumulation at any moment. The derivation of the hazard standard, however, assumes that conditions in the home are relatively static, so the steady state solution to the above equations can capture the long-term air and floor lead and particulate masses. To obtain the steady-state solution for each compartment, the derivative terms are set to zero, so that nothing is changing in time. Using equations (1A) and (2A) to solve for the floor lead mass at steady state gives:

$$FLOOR_{Pb} = \frac{1}{(R + CE \times CF)(AER + D) - RD} \times$$
$$(PbPaintConcen \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) +$$
$$PbSoilConcen \times TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) +$$
$$PbAir \times D \times AER \times P \times V)$$

This equation is linear with respect to the lead paint, soil, and outdoor air concentrations and gives the expected floor lead accumulation in the house at steady state. Similarly, using equations (1B) and (2B) to solve for the floor particulate mass at steady state gives:

$$FLOOR_{Part} = \frac{1}{(R + CE \times CF)(AER + D) - RD} \times$$
$$[CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) +$$
$$TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) +$$
$$PartAir \times D \times AER \times P \times V +$$
$$D \times (CookingRate + SmokingRate + DanderRate)]$$

In order to find the relationship between the floor loading and the concentration, we define the equation:

$$Loading = Slope \times Concen$$

By using the floor lead mass, the floor particulate mass, and the area of the house, the *slope* in the above equation is given by

$$slope = \frac{1}{[(R + CE \times CF)(AER + D) - RD] \times V \times FloorLoading} \times$$
$$[CoverageDens \times ChipFraction \times V \times WallLoading \times UnitConv \times (AER + D) +$$
$$TrackingRate \times \frac{(1 - MatFrac)}{MatFrac} \times (AER + D) +$$
$$PartAir \times D \times AER \times P \times V +$$
$$D \times (CookingRate + SmokingRate + DanderRate)] \qquad \text{(Equation 3)}$$

This final equation is the conversion used in the approach to convert loadings to concentrations (and vice versa).

A.2.1 Input Values for the Mechanistic Model

Values were selected from the literature for input into the mechanistic model equations. Table A-3 lists all the input characteristics in the *slope* variable. The lead paint concentration, lead air concentration, and lead soil concentration are also needed for the calculation of loadings and concentrations, and these are adjusted according to the dataset being modeled. Each variable includes a central tendency estimate intended to be nationally representative. For variables where distribution information is available and implemented in the model, the geometric mean and geometric standard deviation from the estimated lognormal distribution are also shown.

The house volume (*V*) was taken from the 2001 Residential Energy Consumption Survey (RECS) (US DOE, 2001). Binned data were used to estimate the lognormal distribution, and the central tendency estimate is the mean of the calculated distribution. The wall loading (*WallLoading*) and floor loading (*FloorLoading*) were taken from the Exposure Factors Handbook (USEPA, 1997a).

The air exchange rate (*AER*) was taken from the Exposure Factors Handbook (USEPA, 1997a) recommendation. Other information by time of year and region of the country is available, but these data have not been added to the model. The penetration efficiency (*P*) has been modeled for particles of various size classes and has been measured in a few field studies to be less than one (e.g., Dockery and Spengler, 1981; Freed et al., 1983; Liu and Nazaroff, 2001). Unlike the above studies, however, in a field study that simultaneously controlled for penetration and deposition, the penetration efficiency was found to be near 1 for all size classes (Thatcher and Layton, 1995); similar results were also reported for $PM_{2.5}$ for homes in California (Ozkaynak et al., 1996) and for a model of NHEXAS Midwest homes (P=0.96; Layton and Beamer, 2009). Thus, the penetration efficiency was set to 1 for the mechanistic model.

The deposition rate (*D*) was set to 0.65 h^{-1} based on information in the Exposure Factors Handbook (USEPA, 1997a) based on a paper by Wallace (1996). The value for PM_{10} was selected, as most of the suspended particulate in the home is expected to fall within this size range.

The resuspension rate (*R*) varies strongly according to what activity is being undertaken in the home. Resuspension rates during periods where humans are still or absent are lower than during periods of human activity. Vacuuming, in particular, introduces much higher resuspension. For the approach model, an intermediate value was taken from values calculated in Layton and Beamer (2009) for homes in the NHEXAS Midwest region (1.4 x 10^{-4} h^{-1}). This value incorporates the increased resuspension rate during an episode when one person was walking through the room.

An extensive literature review was conducted, but no information could be found for typical paint chipping rates in homes. A few approaches were implemented in the model, including a constant rate, a rate that was exponential in time, and a rate that depended on the overall wall area. Based on a review of the results of the calibration exercise and further review of the physical processes, the latter approach was selected. The chipping fraction was then found by calibrating the mean model predictions against the HUD dataset, as discussed in section A.2.2. The value found to best fit the data was 0.0015% of the wall surface area per year. The coverage density was estimated based on information in EPA's Wall Paint Exposure Model (USEPA, 2001).

As discussed above, the tracking flux (*TrackingFlux)* is parameterized based on information in Von Lindern et al. (2003) and Thatcher and Layton (1995). Von Lindern et al. (2003) measured the amount of particulate deposited on front mats in 276 houses in two locations near the Bunker Hill Superfund Site. The lead levels reported in the paper are expected to be high-end and are not expected to represent general population exposures. This approach assumed, however, that the rate of accumulation of dust on doormats is not strongly affected by the location and can be used to represent a national population of homes. A distribution was developed by combining the data in the two locations in the 1998 site-wide analysis and estimating a geometric mean and geometric standard deviation for the pooled data. The central tendency estimate is the average of the estimated distribution. In addition, Thatcher and Layton (1995) measured the difference between particulate accumulation in tracked and untracked areas in the home as well as the amount on the front mat. This approach assumed that 75% of the home will contain tracked dirt, and the other 25% consists of corners or other less accessible areas in which people do not walk as frequently. Based on this assumption and the information about the amount of mass on the front mat, the tracked areas of the home, and the untracked areas of the home in Thatcher and Layton (1995), 10% of mass on shoes remains on the front mat (*MatFrac*) and 90% is carried into the homes. Such an assumption may be particularly reasonable in homes with children, as children are less likely than adults to wipe their feet carefully as they enter the home. Previous assessments have used different assumptions. The DIRT model (Johnson, 2008) assumed that the mass capture on the mat in the von Lindern study represented the total mass entering the home. For that model, a range of 50-300 mg/day was reported, and a mass flux of 200 mg/day was assumed for urban environments. This is lower than the average of approximately 1,100 mg/day in the current approach. As will be discussed below, however, this higher mass flux is in more agreement with the relative contribution to dust from outdoor soil reported in Adgate et al. (1998) and the average organic fraction in dust.

Cleaning efficiency (*CE*) has been found to vary according to the type of flooring (carpeting versus hard floor) and the total amount of lead on the floor (lower efficiencies for very low lead loadings, due to electrostatic forces attracting the particles to the floor or burial of lead deep into carpet, and higher efficiencies for higher lead loadings). The Environmental Field Sampling Study (EFSS), Volume I: Table 8D-3 (USEPA, 1997b) provides pre- and post-cleaning lead loading estimates from a house with hard floors that was subject to a renovation activity and post-activity cleaning. Thus, these estimates likely are higher than routine cleaning efficiencies in a house where no renovation (and no associated elevated lead loading) has occurred. The selected value for *CE* (12.5% removal with each cleaning) represents an approximate midpoint in the lowest lead loading range in the study. These values are similar to values found by Ewers et al. (1994) and Clemson Environmental Technologies Laboratory (2001) for cleaning efficiencies on a carpeted floor after a renovation activity and after three previous cleaning iterations (so that much of the renovation-related lead loading had already been removed and the cleaning was similar to a routine cleaning). The range of efficiency in the literature varies widely. Bero et al. (1997) reported efficiencies of 50% for carpeted areas and 95% for hard floors, representing high-end estimates of efficiency. Roberts et al. (1994), as cited in Qian et al. (2008), reported efficiencies of only 5-10% in older carpets after lead dust exposure. In addition, Ewers et al. (1994) reported that cleaning must be thorough and be carried out for 6 m^2/min to ensure removal of more than 70% of dust from carpets. Qian et al. (2008) assumed efficiencies of 5% based on a lower vacuuming rate of 1 m^2/min, making the assumption that the 6 m^2/min vacuuming rate is rarely achieved in practice.

Cleaning frequency (*CF*) represents a particularly sensitive variable, as will be discussed in section A.2.3. Self-reported cleaning frequency information was listed in the Exposure Factors Handbook (USEPA, 1997a) for 4,663 U.S. households. The respondents were asked to answer whether they swept or vacuumed nearly every day, three to five times a week, once or twice a week, once or twice a month, less often, or never. Table A-4 lists the data reported in the survey, and the respondents who reported they never cleaned or did not know were not used in the analysis. An upper bound was assigned to each bin and a geometric mean and geometric standard deviation for the overall data were estimated by calculating the distribution that minimized the squared errors between the actual and predicted cumulative probability distributions. The central tendency estimate is the average frequency in the calculated distribution. This value may indicate more cleanings than are realistic, since the data were self-reported; however, this dataset represents the most reliable one that could be located in the literature.

Overall, the selected cleaning efficiency may represent a value toward the lower bound of available values while the average cleaning frequency may be on the higher end (that is, fewer days between cleanings). This observation may reflect the fact that cleanings that occur more often may not be as thorough and may result in lower efficiencies. One way to cast the overall cleaning removal within the context of other models is to examine the cleaning transfer coefficient, which is defined as the cleaning efficiency divided by the days between cleanings. Table A-5 presents information comparing the cleaning removal rate from the current approach model to other models in the literature. Overall, the cleaning removal rate is on the low end of the literature values but is within the range of available values. The table also highlights the wide uncertainty and/or variability associated with this variable. The approach model attempts to address this variability by sampling the cleaning frequency distribution.

Emissions rates for the generation of particulate due to cooking were taken from the “Indoor Air Quality: Residential Cooking Exposures” final report (State of California’s Air Resources Board (CARB, 2001)). Experiments in the CARB study included both cooking episodes and oven cleaning; these were separated and oven cleaning was not included in the analysis. The cooking episodes tested tended to include fairly labor-intensive cooking activities such as frying and broiling meat, and the tests were performed on both electric and gas stoves and ranges. A lognormal distribution was estimated by weighting each experimental cooking test equally to calculate the geometric mean and geometric standard deviation of emissions rates.

Emission rates due to the formation of human dander were taken from Gilbert (2003), who reported that the average human generates 1.5 grams of dander per day. The 2001 RECS (USDOE, 2001) was used to determine that the average U.S. household has 2.2 people in it. This number was rounded to three and multiplied by the amount of dander generated by each person per day. In addition, information from the CHAD database indicated that people tend to spend 2/3 of their time in the home and 1/3 outside the home on average. Thus, it was assumed that only 2/3 of the dander was emitted in the home. The final estimate, then, incorporates these three assumptions.

The assumption was made that the household members do not smoke in their home. A future refinement to the model could include distributions of smoking generation rates based on the frequency of smoking and assumptions about the number of smokers who smoke in their home as opposed to outdoors.

Finally, the outdoor air particulate rate was determined by examining PM_{10} data from particulate monitors in the AQS monitoring network (USEPA, 2010). Data from 1997 were used to match the calibration data sets (see section A.2.2). In general, the particulate mass does not vary as strongly from location to location as the lead mass in the particulate. Thus, the model uses only a central tendency estimate for the particulate concentration based on the average annually-averaged concentration across the AQS monitors.

Table A-3. Input Values for the Mechanistic Model

Variable	Variable Name	Units	Central Tendency Value	Geometric Mean	Geometric Standard Deviation	Source
V	House Volume	m^3	507	390.5	2.06	US DOE (2001)
FloorLoading	Floor area per unit volume	m^2/m^3	0.36	N/A	N/A	US EPA (1997a)
WallLoading	Wall area per unit volume	m^2/m^3	0.98	N/A	N/A	US EPA (1997a)
AER	Air Exchange Rate	h^{-1}	0.63	N/A	N/A	US EPA (1997a)
P	Penetration Efficiency	unitless	1	N/A	N/A	Thatcher and Layton (1995)
D	Deposition Rate	h^{-1}	0.65	N/A	N/A	Value for PM10, US EPA (1997a), adapted from Wallace (1996)
R	Resuspension Rate	h^{-1}	1.4E-04	N/A	N/A	Qian et al. (2008)
ChipFraction	Fraction of wall area that flakes per year	$year^{-1}$	1.50E-05	N/A	N/A	Calibrated
CoverageDensity	Paint Coverage Density	g/m^2	1.25E+02	N/A	N/A	Estimated from paint density and EPA Wall Paint Exposure Model coverage default (US EPA, 2001)
TrackingRate	Tracking Rate	g/day	1.21E-02	7.89E-02	2.52	Von Lindern et al. (2003)
MatFrac	Fraction of tracked material remaining on the mat	unitless	0.1	N/A	N/A	Estimated based on data in Thatcher and Layton (1995)
CE	Cleaning Efficiency	unitless	0.125	N/A	N/A	Estimated based on data in Battelle Memorial Institute (1997)
CF	Cleaning Frequency	days between cleanings	3.5	3.27	1.78	US EPA (1997a)
CookingRate	Cooking Rate	g/day	0.35	N/A	N/A	CARB (2001)
DanderRate	Dander Rate	g/day	3.015	N/A	N/A	Estimated from information in Gilbert (2003)
SmokingRate	Smoking Rate	g/day	0	N/A	N/A	Assumption
PartAir	Outdoor Air Particulate Concentration	g/m^3	2.36E-05	N/A	N/A	Based on analysis of AQS data (US EPA, 2010)

Table A-4. Cleaning Frequency Data from the Exposure Factors Handbook

Frequency	Number Of Respondents	Percentage
Nearly Every Day	921	20%
Three to Five Times a Week	1108	24%
Once or Twice a Week	2178	47%
Once or Twice a Month	373	8%
Less Often	48	1%
Never	10	0%
Did Not Know	25	1%

Table A-5. Comparison of Cleaning Transfer Coefficients in Mass Balance Models

	Cleaning Efficiency (unitless)	Days Between Cleanings (d)	Transfer Coeff (d^{-1})
Layton and Beamer (2009)	N/A	N/A	5.30E-03
Qian et al. (2008)	0.05	7	7.14E-03
Approach Model	**0.125**	**2.5**	**5.00E-02**
Johnson (2008)	0.725	14	5.18E-02

A.2.2 Sensitivity Analysis

In order to determine the parameter values to which the model predictions are most sensitive, a preliminary sensitivity analysis was carried out. First, the media concentrations and other sampled variables were set to their mean values for the HUD dataset. Then, each variable was separately increased by 5% to determine the percent change in the floor loading, the floor concentration, and the slope. The percent changes were then divided by the percent change in the input (5%) to derive the elasticities. Comparison of the absolute value of elasticities across the different variables provides information about the variables to which the model is most sensitive.

Table A-6 shows the elasticities for each variable, where the table is sorted in decreasing order by the absolute value of the slope elasticities. None of the elasticities is greater than 1, indicating that changing a variable by 5% changes the slope by less than +/- 5%. The model is most sensitive to the cleaning frequency, the floor loading, the house volume, and the cleaning efficiency. To date, the model samples the cleaning frequency, but not the other three variables. The literature does not currently have reliable information to allow building a distribution of cleaning efficiencies. The sensitivity analysis, however, suggests that the model should sample both house volume and floor area loading in a future implementation in order to capture the variability in these variables. The model also displays moderate sensitivity to the dander generation rate, the fraction of material staying on the floor mat, the soil tracking rate, the deposition rate, and the air exchange rate.

Table A-6. Elasticities for Each Variable in the Model

Variable	Variable Description	Floor Loading	Floor Concen.	Slope
CF	Cleaning Frequency	0.97	0.00	**0.97**
FloorLoading	Floor Area Loading	-0.95	0.00	**-0.95**
V	House Volume	-0.30	0.66	**-0.93**
CE	Cleaning Efficiency	-0.92	0.00	**-0.92**
DanderRate	Dander Rate	0.00	-0.52	**0.53**
MatFrac	Fraction of tracked material remaining on the mat	-0.33	0.07	**-0.40**
TrackingRate	Tracking Rate	0.31	-0.06	**0.38**
D	Deposition Rate	0.10	-0.21	**0.31**
AER	Air Exchange Rate	0.07	0.36	**-0.29**
CookingRate	Cooking Rate	0.00	-0.06	**0.06**
R	Resuspension Rate	-0.03	0.00	**-0.03**
PartAir	Outdoor Air Particulate Concentration	0.00	-0.03	**0.03**
WallLoading	Wall area per unit volume	0.52	0.52	**0.00**
ChipFraction	Fraction of wall area that flakes per year	0.52	0.52	**0.00**
CoverageDensity	Paint Coverage Density	0.00	0.00	**0.00**
PbAirConcen	Ambient Air Lead Concentration	0.17	0.17	**0.00**
PbSoilConcen	Soil Lead Concentration	0.31	0.31	**0.00**
PbPaintConcen	Paint Lead Concentration	0.52	0.52	**0.00**

A.2.3 Calibration and Comparisons to Datasets

Two datasets were identified for use in calibrating and evaluating the model for residences. The first is the HUD survey of lead in homes (USEPA 1998). This survey provides paint concentrations (as XRF readings), yard soil concentrations, indoor dust lead loading wipe samples and indoor dust lead concentrations for 284 homes. These homes, when combined with their respective weights, are intended to be nationally representative of lead levels in the US housing stock in 1997.

In order to compare the model predictions to the survey results, the AQS data were used to estimate the distribution of lead in total suspended particles (TSP) in 1997 (USEPA, 2010). Available lead monitoring results were averaged to give yearly averages and a lognormal distribution was developed based on the range of values across the different monitors. In addition, distributions of paint concentration and soil concentration were developed from the HUD data from homes built before 1980. The model was then run under the assumption of three different cleaning frequencies (once a week, twice a week, and twice a month) based on the range of cleaning frequencies in the Exposure Factors Handbook (USEPA, 1997a). To generate each of the 100 model points, the soil, paint, and air concentration distributions were sampled to generate a combination of estimates, and the model equations were applied to calculate the floor loading and the slope. Figure A-3 shows the lead loadings and corresponding concentrations for the HUD data and the model predictions. The regression equation discussed in Section A.1 is also shown for reference.

For a given cleaning frequency, the mechanistic model predictions fall in a straight line defined by the slope equation above. Because this equation does not depend on the soil, paint, and air concentrations and because nothing else was sampled in the development of the figure, the slope is constant for a given cleaning frequency. The slope tends to decrease in homes in which cleaning occurs less frequently. The national average cleaning frequency in the Exposure Factors Handbook is approximately two cleanings per week; thus, the paint flaking fraction variable (*ChipFraction*) was adjusted until the slope was in good agreement with the regression line for loadings up to the 75^{th} percentile loading (a value of approximately 17.3 μg/ft^2). Note that the other two cleaning frequencies represent high and low bounds estimates for the population (cleaning every day represents the 2^{nd} percentile while cleaning once every two weeks represents the 99.5^{th} percentile from the estimated cleaning frequency distribution) and they bound the majority of the loading and concentration data points.

The model predicts a straight line for a given cleaning frequency, while the regression suggests a nonlinear relationship. One possible interpretation of this discrepancy is that most of the higher loadings likely occur in homes which are vacuumed less often. Thus, as one moves along the loading axis, a change in cleaning frequency leads to a change in the slope of the loading-concentration relationship.

Once this initial calibration step was complete, the model was run again by sampling additional variables where distributions existed; thus, in addition to the soil, paint, and air concentrations, the soil tracking rate and cleaning frequency were also sampled. The resulting model points are shown along with the raw HUD data in Figure A-4. These model values provide a suitable spread across the actual data. In order to quantify the model performance, Table A-7 provides a comparison of the average and median loadings and concentrations. The model tends to underpredict the mean loadings and concentrations; the means are more affected by the outliers, suggesting that the central tendency values used for most variables may not be sufficient to capture the very high loadings and concentrations. The model is able to capture the median loadings and concentrations, however, which still reflect the distribution, but are not as affected by outliers.

Table A-8 compares model metrics to values found in the literature for data or from other models. Adgate et al. (1998) provided estimates of the fraction of the loading arising from the air, soil, and paint sources in homes in Jersey City, NJ. The model tends to predict more lead arising from paint sources and less from soil sources than in the Adgate study. The Jersey City homes in the Adgate study, however, tended to be in urbanized areas with higher average soil concentrations than in the nationally-representative HUD dataset. Also shown is the average indoor/outdoor air ratio in 35 California homes for PM_{10} from Colome et al. (1992). The model predicts a ratio very close to this value, which provides further support to the fact that the model parameters are not merely tuned, but may be reflecting the actual physical processes at work in the homes. The model predicts that about 66% of indoor dust mass arises from indoor sources of organic material (e.g., cooking, human dander). After analyzing the dust in four homes in England, Allott et al. (1994) concluded that 42% +/- 17% arose from organic sources. This suggests the model prediction is within the range found in the four homes in the study and lends support to the relative contribution from soil, paint, air, and indoor sources to indoor dust.

Figure A-3. Modeled Loading-to-Concentration Relationships for Three Different Cleaning Frequencies

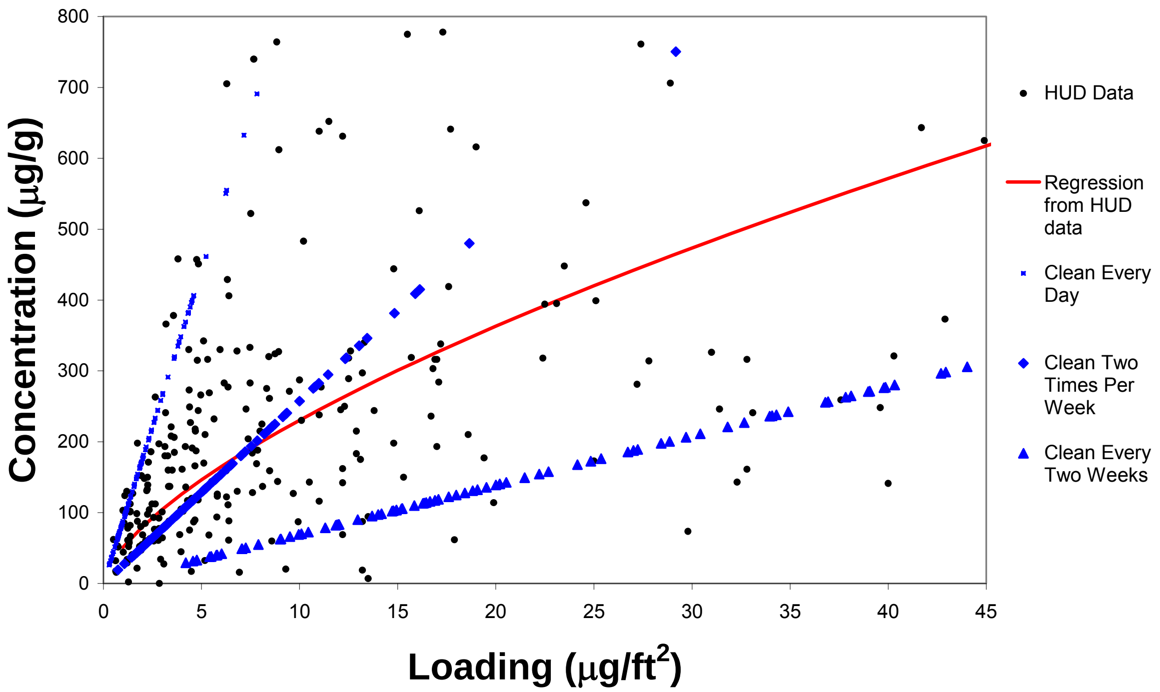
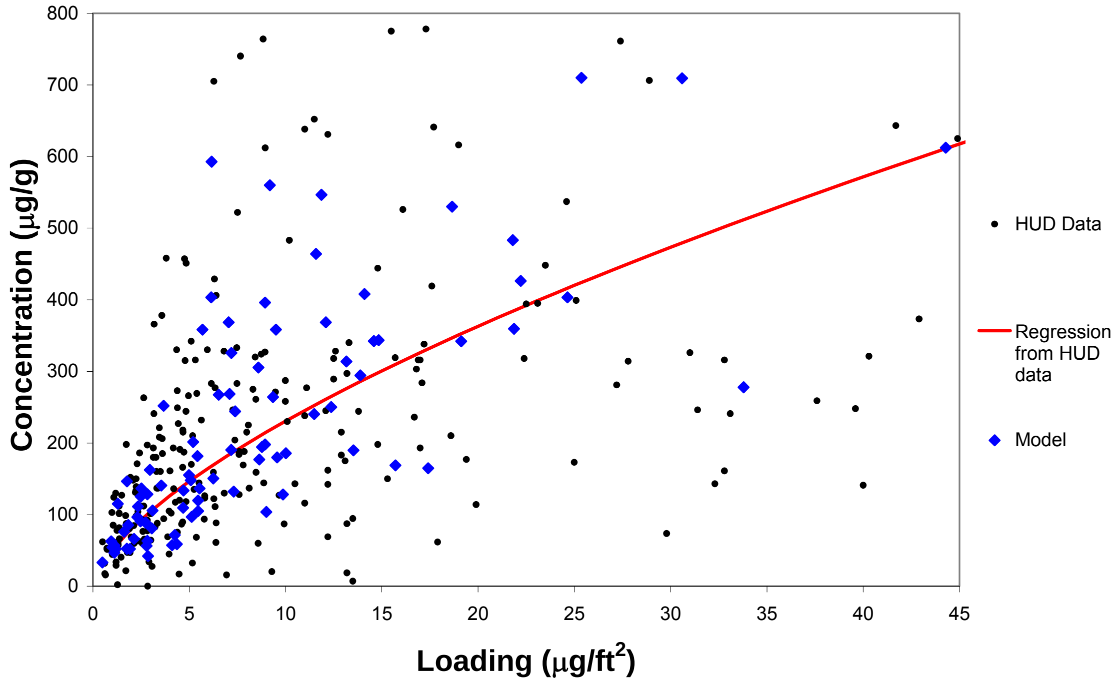


Figure A-4. Modeled Loading and Concentration Values Using HUD Air, Paint, and Soil Distributions and Distributions for Soil Tracking and Cleaning Frequency



1

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Table A-7. Comparison Between Modeled and Actual Loadings and Concentrations

	Mean Load	Mean Concen	Median Load	Median Concen
HUD Data	21	559	7.4	201
Model	13	336	7.3	188

Table A-8. Comparison Between Modeled and Actual Loadings and Concentrations

	% Air	% Soil	% Paint	Indoor / Outdoor Air Ratio	% Indoor Dust from Organic Sources
Literature	17%[a]	49%[a]	34%[a]	0.7[b]	42% +/- 17%[c]
Model	38%	13%	49%	0.63	66%

[a] From Adgate et al. (1998)
[b] From Colome et al. (1992)
[c] From Allott et al. (1994)

Once the calibration was complete, the model was applied to a second dataset as a further model evaluation. Lanphear et al. (1998) collected data for 205 children in Rochester, NY. As part of the blood lead evaluation, they collected wipe lead dust loading samples, lead concentration samples, indoor XRF lead paint concentrations, and play yard and house perimeter lead soil samples. Samples were collected in multiple areas and a composite was estimated as the average or median sample value. Distributions were generated from the lead paint concentrations and play yard soil lead concentrations for use in the model. It was assumed that the play yard soil would be more readily tracked into the home than the house perimeter soil. The AQS monitoring network was used to calculate lead concentrations in the ambient air. A distribution was generated by finding the monthly average concentrations for data from 1993-1996 and finding the geometric mean and geometric standard deviation. The model was then applied to the dataset with no other modifications. The lead air concentration, lead soil concentration, lead paint concentration, soil tracking rate, and cleaning frequency were all sampled and modeled for 100 realizations and compared to the median of the floor lead loading and concentration estimates. Figure A-5 provides a comparison between the modeled and actual data. As in the HUD dataset, the spread and pattern of modeled data are consistent with the actual data. Note that the spread of the data is larger in the Rochester data than in the HUD data, likely due to much larger average soil concentrations. Also shown for reference is the regression line calculated from the HUD data and the regression line calculated directly from the Rochester data. The regression lines predict similar relationships at higher loadings, but differ by 25-50% for loadings between 10 and 40 $\mu g/ft^2$.

Table A-9 compares the modeled and actual means and medians along with the source contribution percentages and outdoor/indoor air ratios. Overall, the model does well at predicting the medians, although it tends to underpredict the means as in the HUD dataset. Table A-10 compares other model metrics to the values in the literature. The source percentages are more similar to the Adgate data (1998), perhaps because the Rochester homes are more comparable with the Adgate Jersey City homes; however, the model still tends to contribute more from paint and less from soil than the Adgate data suggest. The indoor/outdoor ratio is still within range of the mean value from Colome et al. (1992). The percentage of dust mass arising from indoor sources is the same as in the HUD model, since this value does not rely on any of the lead media concentration values.

Figure A-5. Modeled Loading and Concentration Values Using Rochester Air, Paint, and Soil Distributions and Distributions for Soil Tracking and Cleaning Frequency

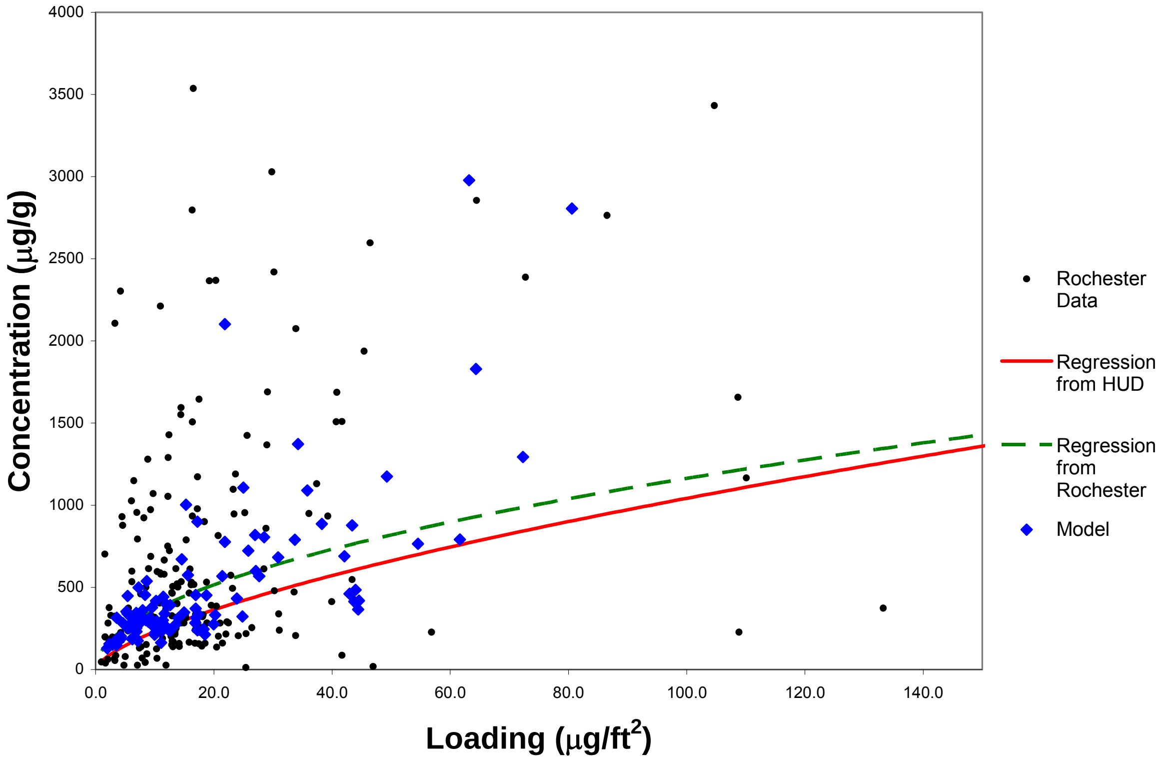


Table A-9. Comparison Between Modeled and Actual Loadings and Concentrations

	Mean Load	Mean Concen	Median Load	Median Concen
Rochester Data	21	776	14	370
Model	20	590	13	342

Table A-10. Comparison Between Modeled and Actual Loadings and Concentrations

	% Air	% Soil	% Paint	Indoor / Outdoor Air Ratio	% Indoor Dust from Organic Sources
Literature	17%[a]	49%[a]	34%[a]	0.7[b]	42% +/- 17%[c]
Model	16%	27%	57%	0.63	66%

[a] From Adgate et al. (1998)
[b] From Colome et al. (1992)
[c] From Allott et al. (1994)

A.3 Strengths and Limitations of the Loading-Concentration Conversion Models

As discussed in Section 2.3.2, each of these two alternative methods to convert the loadings to concentrations has strengths and limitations. The regression equation is based on a nationally-representative dataset with sufficient samples across different housing vintages, outdoor soil concentrations, and indoor paint concentrations. The regression equation is most reliably applied in the range of loadings and concentrations seen in the original dataset, and the hazard standard is expected to fall within that range. The equation is specific to residences, however, and cannot be easily extended to public and commercial buildings (see Section 3.2.3). In addition, the regression equation does not allow any incorporation of variability due to the difference in physical attributes and cleaning patterns among homes. The underlying data show a wide spread across the loading-concentration parameter space, indicating wide house-to-house variability (see Appendix A).

The mechanistic model, on the other hand, allows for extension of the model to public and commercial buildings, provided the physical processes are described adequately and the proper input values can be developed. Because the public/commercial buildings tend to be larger, more people come in and out of the buildings daily (thus introducing more dander to the indoor environment and diluting the indoor dust), and the cleaning patterns are different, these buildings can be expected to have a very different loading-to-concentration relationship than houses. However, the model assumes that the indoor environment is well-mixed and contains no concentration gradients; thus, it can be applied to any portion of the public/commercial building where this assumption is valid. The mechanistic model also allows for the loading to concentration conversion to incorporate house-to-house variability. The model is subject to uncertainty, however, because of the relatively simple form of the physical equations and the absence of information about some of the variable inputs. The model has been calibrated against the HUD dataset and then compared to one additional dataset, and the model is expected to return reasonable estimates for the national population in the range of the hazard standard. There currently is no relationship between window sill loading and concentration, however, and unless such a slope is developed, the same slope as used for the floor dust would have to be used in developing the window sill hazard standard.

In addition, the mechanistic model uses the steady state solution to the model equations. One assumption is made in the development of these equations, however, which affects the solution. When the steady state equations are solved, an assumption is made that routine cleaning happens continuously at a rate equal to the cleaning frequency. In reality, however, the cleaning occurs in discrete episodes once per cleaning cycle. This assumption introduces some error into the slope, loading, and concentration estimates, and this error increases with increasing numbers of days between cleaning. Table A-11 shows a representative sample of the slope and loadings under the assumption of episodic and continuous cleaning for ten of the 200 model realizations. For cleaning every two weeks, the error in the slope is up to 14.5%; however, at the average cleaning frequency (about two cleanings per week), the error is only an average of 7.0% (maximum of 9.5%). The errors in the loadings are comparable, and the errors in the concentrations are only an average of 0.5% (maximum of 0.7%). Thus, this assumption, which is necessary from a practical standpoint in the development of the hazard standard in order to avoid numerous iterations of the model, introduces reasonable error in the region of anticipated cleaning frequencies.

While attempts have been made to take into account variability across homes by sampling some of the input parameters, no attempt has been made to account for variability within a home. Unlike the DIRT model (Johnson, 2008), which predicts gradients across floors and carpets, the model treats the home as a uniform environment. Differences across carpets and floors and between high traffic areas and less accessible areas are not accounted for in the model, and the assumption is made that the model captures the mean characteristics of the heterogeneous home.

Table A-11. Representative Realizations Demonstrating the Error When Considering Continuous Cleaning Compared to Episodic Clea

Reali-zation	Outdoor Air Concen. (μg/m3)	Soil Concen. (μg/g)	Paint Concen. (μg/g)	Tracking (g/day)	Clean. Freq. (days between clean.)	Floor Loading, Episodic Clean.	Floor Concen, Episodic Clean.	Slope, Episodic Clean.	Floor Loading, Contin. Clean.	Floor Concen. Contin. Clean.	Slope, Contin. Clean.	% Error in Load.	% Erro in Conce
1	9.39E-02	1.39E+02	1.11E+00	9.50E-02	2.38E+00	6.04E+00	2.69E+02	2.25E-02	6.45E+00	2.67E+02	2.42E-02	6.8%	-0.5
5	4.12E-02	6.80E+01	2.10E+00	1.78E-02	3.74E+00	7.93E+00	3.08E+02	2.58E-02	8.43E+00	3.06E+02	2.76E-02	6.3%	-0.7
9	4.32E-03	9.61E+00	2.53E+01	1.20E-01	9.47E-01	1.80E+01	1.81E+03	9.96E-03	1.92E+01	1.80E+03	1.07E-02	6.5%	-0.5
13	2.50E-02	4.41E+01	8.20E-01	1.33E-01	2.52E+00	2.87E+00	1.06E+02	2.70E-02	3.06E+00	1.06E+02	2.89E-02	6.5%	-0.4
17	4.82E-02	7.79E+01	1.69E+00	2.79E-01	5.72E+00	1.44E+01	1.69E+02	8.49E-02	1.53E+01	1.69E+02	9.05E-02	6.3%	-0.3
21	2.04E-02	3.69E+01	9.95E-01	3.10E-02	3.15E+00	3.28E+00	1.42E+02	2.32E-02	3.49E+00	1.41E+02	2.48E-02	6.6%	-0.6
25	3.06E-03	7.11E+00	2.96E-01	5.28E-02	1.70E+00	4.66E-01	3.34E+01	1.39E-02	4.97E-01	3.32E+01	1.50E-02	6.6%	-0.6
29	2.41E-02	4.27E+01	9.28E-01	7.75E-02	2.05E+00	2.30E+00	1.26E+02	1.83E-02	2.46E+00	1.25E+02	1.96E-02	6.7%	-0.5
33	1.49E-01	2.07E+02	6.02E-01	4.05E-02	3.18E+00	8.78E+00	3.60E+02	2.44E-02	9.34E+00	3.58E+02	2.61E-02	6.4%	-0.6
37	4.34E-01	5.24E+02	1.38E+00	5.50E-02	1.80E+00	1.44E+01	9.76E+02	1.48E-02	1.54E+01	9.70E+02	1.59E-02	6.9%	-0.6
41	3.62E-02	6.08E+01	8.21E-01	1.27E-01	1.93E+00	2.63E+00	1.29E+02	2.04E-02	2.80E+00	1.28E+02	2.18E-02	6.4%	-0.4
45	9.97E-03	1.98E+01	1.26E+00	5.72E-02	6.35E+00	6.67E+00	1.33E+02	5.02E-02	7.08E+00	1.32E+02	5.36E-02	6.2%	-0.6
51	2.38E-02	4.22E+01	3.69E+00	1.46E-01	1.50E+00	4.80E+00	2.91E+02	1.65E-02	5.24E+00	2.90E+02	1.81E-02	9.1%	-0.4
55	7.05E-02	1.08E+02	6.93E-01	2.47E-02	1.95E+00	3.10E+00	2.19E+02	1.42E-02	3.30E+00	2.17E+02	1.52E-02	6.7%	-0.7
59	7.43E-02	1.13E+02	8.81E-01	1.26E-01	1.36E+00	2.97E+00	2.05E+02	1.45E-02	3.16E+00	2.04E+02	1.55E-02	6.5%	-0.5
63	2.70E-01	3.48E+02	8.28E-01	2.70E-02	8.63E+00	3.76E+01	6.42E+02	5.86E-02	3.99E+01	6.38E+02	6.25E-02	6.1%	-0.6
67	1.68E-02	3.12E+01	2.12E+00	3.84E-02	3.03E+00	5.52E+00	2.39E+02	2.31E-02	5.86E+00	2.37E+02	2.47E-02	6.2%	-0.6
71	1.13E-01	1.64E+02	2.74E+00	4.59E-02	4.44E+00	1.66E+01	4.85E+02	3.42E-02	1.77E+01	4.82E+02	3.67E-02	6.5%	-0.6
75	1.50E+00	1.54E+03	1.43E+00	9.95E-02	6.89E+00	1.77E+02	2.80E+03	6.31E-02	1.88E+02	2.79E+03	6.72E-02	6.1%	-0.5
79	7.27E-02	1.11E+02	3.63E+00	4.01E-02	8.42E+00	3.00E+01	4.95E+02	6.06E-02	3.18E+01	4.92E+02	6.47E-02	6.1%	-0.6
83	2.24E+00	2.18E+03	9.50E-01	6.81E-03	2.94E+00	9.48E+01	4.89E+03	1.94E-02	1.01E+02	4.86E+03	2.08E-02	6.4%	-0.7
87	1.38E-03	3.57E+00	2.60E+00	1.63E-01	5.21E+00	9.80E+00	1.66E+02	5.89E-02	1.04E+01	1.66E+02	6.29E-02	6.3%	-0.4
91	7.98E-01	8.90E+02	4.50E+00	7.50E-01	5.79E+00	2.00E+02	1.17E+03	1.71E-01	2.13E+02	1.17E+03	1.81E-01	6.1%	-0.2
95	1.66E-01	2.27E+02	6.24E-01	5.89E-02	2.83E+00	9.01E+00	3.85E+02	2.34E-02	9.61E+00	3.83E+02	2.51E-02	6.7%	-0.6
100	1.26E-01	1.79E+02	1.25E+00	1.01E-01	2.29E+00	7.48E+00	3.36E+02	2.22E-02	7.96E+00	3.34E+02	2.38E-02	6.4%	-0.5

A.4 Regression Relationship for Floor and Sill Dust Loadings

The National Survey of Lead-Based Paint in Housing ("HUD Survey Data") was used to develop an empirical relationship between floor and window sill dust loadings. As discussed in Section A.1, in order to focus on the homes containing lead paint, only the data from the first three vintage categories were included. From the raw data, each floor and window sill dust loading was transformed by taking the natural log. Then, the regression was carried out using the untransformed variables and also the natural-log-transformed variables. Table A-12 shows the results of each regression.

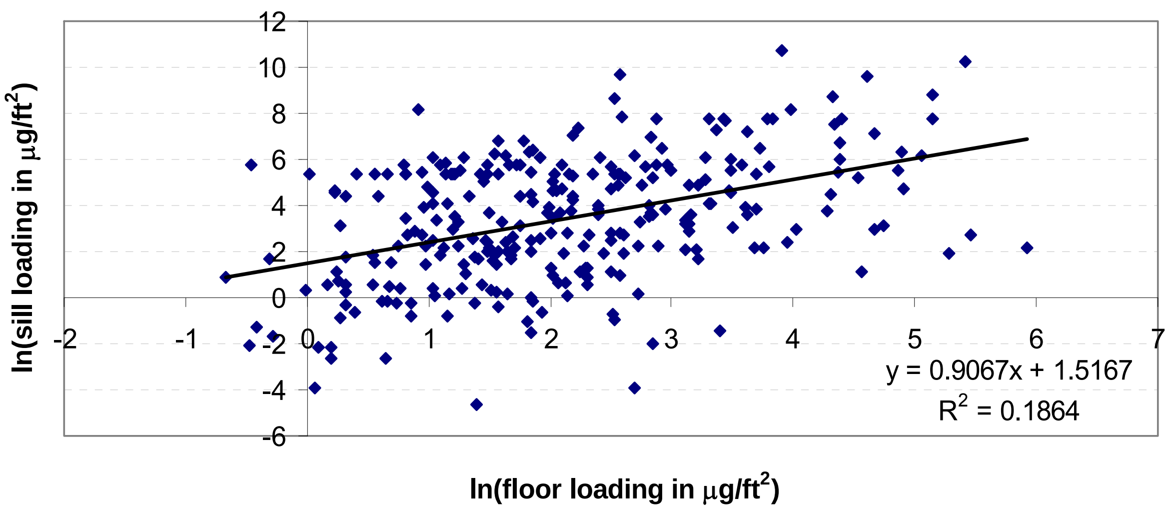
Table A-12. Regression Analysis Results

Data	Variable	Coefficient	Standard Error of Coefficient	t-stat	p-value	F-stat, p-level	Adjusted R^2
Untransformed	Intercept	203.8	219.6	0.93	0.35	20.5, <0.001	0.064
	Slope	21.7	4.8	4.5	<0.001		
Natural-log-transformed	Intercept	1.52	0.28	5.44	<0.001	64.6, <0.001	0.186
	Slope	0.91	0.11	8.04	<0.001		

The data are positively skewed, and the regression analysis reveals that the log-transformed data appear more highly correlated, with a greater adjusted R^2. Thus, the transformed relationship is chosen, and Figure A-6 shows the data and the regression equation. The equation relating the two loadings would then be

$$Sill = 4.56 \times Floor^{0.91}.$$

Figure A-6. Regression Relationship between Ln(Sill) and Ln(Floor) for the HUD Data



As an alternative method, Lanphear et al. (1998) collected data for 205 children in Rochester, collected in multiple locations and arithmetic and geometric averages were calculated. For the floor to sill relationship, the geometric means of floor and sill loadings were selected since they are not as susceptible to outliers within the house. As with the HUD data, regressions were performed on both the untransformed and natural-log-transformed variables. Table A-13 shows the results of each regression.

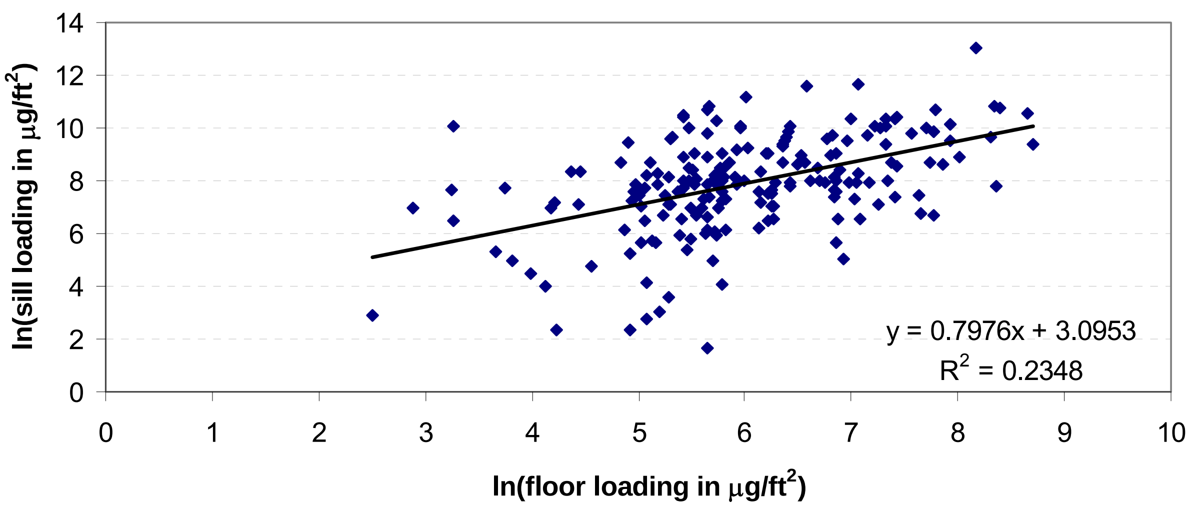
Table A-13. Regression Analysis Results

Data	Variable	Coefficient	Standard Error of Coefficient	t-stat	p-value	F-stat, p-level	Adjusted R^2
Untransformed	Intercept	2583.1	3034.5	0.85	0.40	21.0, <0.001	0.094
	Slope	11.1	2.4	4.58	<0.001		
Natural-log-transformed	Intercept	3.1	0.64	4.86	<0.001	58.9, <0.001	0.234
	Slope	0.80	0.10	7.68	<0.001		

Again, the log-transformed analysis was selected since the variables appear more highly correlated (with a greater adjusted $R^{2)}$, and Figure A-7 shows the data and the regression equation. In this case, the correlation is slightly higher (R=0.48) and the equation relating sill to floor loading would be

$$Sill = 22.1 \times Floor^{0.80}$$

Figure A-7. Regression Relationship between Ln(Sill) and Ln(Floor) for the Rochester Data



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