1	Personal Exposure Monitoring Wearing Protocol Compliance: An Initial
2	Assessment of Quantitative Measurement
3	Phil Lawless <sup>1</sup> Jonathan Thornburg <sup>1</sup> Charles Podes <sup>1</sup> and Pon Williams <sup>2*</sup>
5	This Lawless, Johannan Thomburg, Charles Roues, and Ron withanis
6	<sup>1</sup> RTI International, Research Triangle Park, NC 27709
7	<sup>2</sup> U.S. EPA National Exposure Research Laboratory, Research Triangle Park, NC 27711
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23 24	2* Address all correspondence to: Ron Williams National Exposure Research Laboratory, US
25	EPA MD E-205-04 RTP NC 27711 USA Tel: +1 919 541 2957 Fax: 1 + 919 541 0905 E-
26	mail: <u>williams.ronald@epa.gov</u>
27	
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1 2 Abstract

3 4 Personal exposure sampling provides the most accurate and representative assessment of 5 exposure to a pollutant, but only if measures are implemented to minimize exposure 6 misclassification and reduce confounders that may cause misinterpretation of the collected data. 7 Poor compliance with personal sampler wearing protocols can create positive or negative biases 8 in the reported exposure concentrations, depending on proximity of the participant or the 9 personal sampler to the pollutant source when the monitor was not worn as instructed. 10 This paper presents an initial quantitative examination of personal exposure monitor 11 wearing protocol compliance during a longitudinal particulate matter personal exposure 12 monitoring study of senior citizens of compromise health in North Carolina. Wearing 13 compliance varied between participants due to gender or employment status, but not 14 longitudinally or between cohorts. A minimum waking wearing compliance threshold, 0.4 for 15 this study of senior citizens, is suggested to define when personal exposure measurements are 16 representative of a participant's exposure. The ability to define a minimum threshold indicates 17 data weighting techniques may be used to estimate a participant's exposure assuming perfect 18 protocol compliance. 19

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## 1 2 Introduction

3	Quantification of an individual's exposure to particulate matter (PM) is critical for
4	understanding its effects on their health. Many epidemiologic studies have shown short-term and
5	long-term exposures to ambient PM adversely affects human health and that the increase in the
6	level of exposure is significantly associated with increase in prevalence of mortality (Schwartz,
7	2003) and morbidity (Zanobetti and Schwartz, 2003). PM-health effects were found most
8	consistently in young children who are still under physical development and have physiological
9	differences from adults and in senior citizens who are likely to have pre-existing health
10	conditions.
11	Ambient PM concentrations measured by a centrally located sampler as a surrogate of
12	personal exposure have been used in epidemiological studies to show increases in mortality or
13	morbidity with incremental increases in PM concentration (Dockery et al., 1993). However, the
14	level of representativeness of this exposure surrogate approach is sometimes difficult to define
15	compared to true breathing zone assessments (Rodes and Thornburg, 2004).
16	Stationary samplers located indoors and outdoors to monitor home environments are
17	another approach. For health compromised participants, the local indoor and outdoor exposure
18	measures are expected to provide a more representative assessment of their exposure and a
19	correspondingly stronger association to adverse health effects than would regional sampling. An
20	individual's PM exposure varies according to the presence of nearby outdoor and indoor sources,
21	residential air exchange rate, and fraction of time spent indoors, outdoors, or other indoor
22	environments (Williams et al., 2000a; Rodes et al., 2001; Thornburg et al., 2004; McBride et al.,
23	2007; Williams et al., 2009; Rodes et al., 2010;). This location-time approach relies heavily on

1	the accuracy of the participants' time-activity diary to apportion exposure between indoor and
2	outdoor aerosols. However, this method may miss exposures to sources not being explicitly
3	monitored, such as office, school, or automobile (Wallace and Williams, 2005; Wallace et al.,
4	2006). Additionally, indoor and outdoor measurements miss the "personal cloud", the particulate
5	matter exposures that results from personal activities magnified by their proximity to the source
6	(Rodes et al., 2004). The National Academy of Science designated this bias as "exposure
7	misclassification error" and recommended research was needed to address the development of
8	robust linkages between exposures and health outcomes (NRC, 2004).
9	Personal, breathing zone exposure monitoring is another approach that when applied
10	correctly captures PM exposures in all environments and removes all sampling ambiguities.
11	Various studies have taken different approaches to examine personal PM exposure levels for
12	comparison with outdoor and/or indoor air monitoring data (Janssen et al., 1998; Adgate et al.,
13	2002; Liu et al., 2003; Turpin et al., 2007; Williams et al., 2003a; Williams et al., 2009).
14	Personal exposure monitors collect real-time and time integrated measurements of acute and
15	chronic exposure, respectively. Time-activity diaries are useful for categorizing the immediate
16	environments where exposure occurred and sources of PM, but they do not provide an accurate
17	and representative assessment of exposure.
18	Personal sampling provides the most accurate and representative assessment of PM
19	exposure, but only if measures are implemented to minimize exposure misclassification and
20	minimize data misinterpretation. Rodes et al. (2010) showed that personal monitor wearing
21	protocol compliance violations reduced the accuracy and representativeness of the personal

22 exposure measurements obtained during a general population study in Detroit, MI. The

corresponding associations between the biased PM exposures and adverse health outcomes could
 have been weakened if this had not been accounted for in the analysis (Brook et al., 2010). This
 situation leads to exposure misclassification; the inadvertent attribution of a health effect (or
 absence of a health effect) to a PM concentration and its chemical speciation that is not
 representative of their actual exposure.

6 "Wearing compliance" is defined here as how well a participant wears the personal 7 sampler in accordance with the sampling protocol. This definition is not to be confused with 8 other forms of "compliance" monitoring such as monitoring to determine compliance with 9 regulatory standards (e.g., Chow and Watson, 2008) or respiratory testing protocol compliance 10 (e.g., Delfino et al., 2006). If the participant fails to wear the personal sampler properly for 11 significant time intervals, then the measured concentrations may be artificially low or high and 12 vield exposure misclassification. Conclusions drawn under the assumption that the PM samples 13 represent their actual exposure might represent an entirely different exposure scenario.

14 Participant compliance with study protocols is easily measured by monitoring the 15 movement of the sampler with an embedded sensor. The rationale is that the movement of the 16 monitor and the signal that is recorded are correlated to the participant's movements, with the 17 sensor recording a signal indistinguishable from background signal noise if there is not any 18 movement because the monitor is not being worn. Commercially available 1-, 2-, and 3-axis 19 accelerometer packages, such as the Actical® (Mini Mitter, Bend OR) or HOBO Pendant G 20 (Onset Computer Corp., Bourne MA), or an embedded, bare 3-axis accelerometer chip (e.g., Oki 21 L8950, Tokyo Japan) on a circuit board is one approach to monitor compliance using a small, 22 low power system. Another method uses a co-planar capacitance plates connected to a capacitive sensor in a data logger to detect proximity to the participant's body (Pellizzari et al, 1995;
 Lawless, 2003). Ideally, any sensor used should provide a signal proportional to the participant's
 activity level.

4 Wearing compliance with regard to personal exposure sampling has generally received 5 little attention. Ebelt et al. (2000) used time-activity diaries to verify personal sampler use and 6 found that on average, the samplers were worn for 63 percent of the protocol time. They 7 attributed the non-compliance to the burden of the samplers, even though they described the 8 participants as "highly committed". Delfino et al. (2004, 2006) addressed protocol wearing 9 compliance for specific, technically difficult personal exposure measurements. This research 10 noted the impact of personal monitoring burden on exposure data representativeness, but did not 11 quantitatively account for poor wearing compliance in the data analysis. In the RIOPA study, 12 relatively low-burden small passive samplers were used, but wearing protocol compliance of the 13 samplers was not monitored (Liu et al, 2006; Liu et al, 2007).

This paper presents the first quantitative examination of protocol wearing compliance during a PM personal exposure monitoring study. The influence of protocol compliance on the representativeness of the collected exposure data is discussed. The definition of protocol compliance is refined to consider the events that have the largest impact on a participant's PM exposure. How compliance is measured and the procedures for analyzing compliance data are also presented.

20 Methods

Personal exposure sampler *wearing protocol compliance* is the fraction of time that the
 sampler is worn compared to the time it should have been worn. If a participant follows the

1 protocol and keeps the sampler in their bedroom while sleeping, this period is always considered 2 to be fully compliant. We found participants almost always complied with this portion of the 3 study protocol. Therefore, it is useful to define *waking wearing compliance* as the fraction of 4 time the participant follows the personal exposure monitor sampling protocol while awake. The 5 benefit is that waking wearing compliance maximizes the range (highest to lowest) of 6 compliance measurements for the most compliant and least compliant participants. The 7 amplified range increases the ability to detect statistically significant differences between 8 participants and across longitudinal sampling sessions. Similarly, the term *mass wearing* 9 *compliance* describes the fraction of time the sampler was worn while the PM concentration was 10 within one of several, user-defined mass concentration ranges. This definition considers whether 11 the sampler was worn during peak concentration events that possibly contributed to a substantial 12 portion of the exposure over an entire sampling period.

13 Waking and mass wearing compliance were assessed as part of the U.S. EPA's RTP 14 Particulate Matter Panel Study (Williams et al., 2003a, 2003b). Determination of wearing 15 compliance was performed for subjects completing all four seasons of the monitoring campaign 16 (n=26). Data from five consecutive monitoring days, with daily in-home visits to download 17 personal PM sampler data logger data, retrieve PM<sub>2.5</sub> personal filter samples, and download real-18 time, personal nephelometer were recovered. The personal PM sampler consisted of a two-19 channel, battery-powered sampling system that contained a data logger to monitor personal 20 activity, battery voltage, air temperature, and pump pressure in both channels (Lawless, 2003). 21 The activity monitor used was based on the co-planar capacitance plates approach. PM<sub>2.5</sub> PEM 22 (Personal Environmental Monitor, MSP, Inc.) inlets collected a Teflon filter for gravimetric mass

1 and PM speciation analysis, and a quartz filter for EC (elemental carbon) and OC (organic 2 carbon) analysis. A passive mode MIE personalDataRAM nephelometer (Thermo Fisher Model 3 pDR-1000 uncorrected for aerosol or relative humidity influences and a HOBO H8 (Onset 4 Computer Corporation) measured PM concentration and temperature-relative humidity, 5 respectively (Howard-Reed et al, 2000; Wallace et al., 2006). Participants wore a specially 6 constructed vest that held the PEM inlets near the breathing zone and the nephelometer at waist 7 level. The vest was made of light blue or light gray nylon, weighed 2.5 kg, and pump noise was 8 less than 40 dB. Williams et al. (2003a) provides additional details. The study protocol asked 9 participants to wear the vest at all times, except when sleeping, bathing, or riding in an 10 automobile. In these instances, the vest was to be kept in the same room or within the automobile 11 passenger compartment. Participants were not informed that their compliance with study 12 protocols was being monitored.

13 Waking and mass wearing compliance was calculated from the personal PM sampler 14 logger and nephelometer data. The capacitance sensor movement, data logger temperature, and 15 nephelometer concentration and temperature data were loaded into a Visual Basic program that 16 displayed the traces graphically on a common time scale (Figure 1). The analyst first considered 17 the activity signal (top panel), then the logger pump temperature (second panel), and finally the 18 nephelometer temperature (fourth panel) in deciding whether the sampler was being worn at any 19 time and sleep periods and establishing data inclusion points. The program then calculated the 20 cumulative time contained within the start and end of the waking compliant interval during the 5 21 days of data collection per individual and summarily the waking wearing compliance and mass wearing compliance. The mass wearing compliance ranges selected were  $10-20 \text{ µg/m}^3$ , 20-30 22

1	$\mu g/m^3$ , 30-50 $\mu g/m^3$ , 50-100 $\mu g/m^3$ , and greater than 100 $\mu g/m^3$ . These ranges were based on the
2	distribution of PM concentrations measured with the nephelometer.

Effects of study subjects and monitoring conditions on the waking and mass wearing compliance were investigated using a general linear model (SAS v9.1.3, Cary NC). The type of cohort, season, gender, occupation, PM level, and all interactions of these variables were initially included in the model as independent variables. A second model substituted participant identification number for cohort. To identify a meaningful subset of predictors, non-significant or auto-correlating variables were removed stepwise from the model. The significance of the effect was tested at the 5% level.

#### 10 **Results**

11 Table 1 presents the calculated waking wearing compliance across all seasons for each 12 participant. Table 2 shows the average waking or mass wearing compliance, the average standard deviation in the wearing compliance measurement, and the coefficient of variation (CV) for all 13 participants and seasons calculated by three independent analysts. Coefficients of variation from 14 15 0.21 to 0.28 across the waking and mass wearing compliance assessments provided evidence the 16 three analysts interpreted wearing compliance values from the data logger and nephelometer 17 traces similarly. The consistency in the CVs between the different measures of wearing 18 compliance indicated measurement error did not vary as a function of PM concentration. 19 The statistical analysis results for the two linear models are shown in Table 3. 20 Independent variables in the first model were Cohort, Gender, Occupation, Season, and PM 21 concentration ranges used to define mass wearing compliance. PM concentration range, Gender, 22 and Occupation were statistically significant. Figure 2 shows the increase in wearing compliance

1 as the real-time PM concentration exposure increases. A slight difference in wearing compliance 2 between the two study cohorts might be evident (Figure 3), but the fewer number of participants 3 in the defibrillator cohort cautions against this interpretation. The second model examined 4 differences between individual Participants (ID), Season, PM concentration ranges, ID-Season 5 interaction, and ID-PM range interaction. Wearing compliance values varied between 6 participants and PM concentration range. As with the first model, seasonal variation in wearing 7 compliance was not evident. However, the significant ID-Season interaction (p-value < 0.0001) 8 indicated individual participants exhibited seasonal variations in their wearing compliance. The 9 ID-PM range interaction was not significant.

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### 11 **Discussion**

12 The statistical insignificance of cohort on waking and mass wearing compliance was 13 important. Since participant recruitment for the study used a convenience cohort approach with 14 specific inclusion criteria (Williams et al., 2003a), a difference in wearing compliance between 15 the cardiac defibrillator and hypertensive cohorts was expected. We theorized the defibrillator 16 cohort would be more compliant because of their more compromised health status and their 17 overall enthusiasm as participants in the research. The general trend does show that compliance 18 with study protocols might be related to the participant's interest in the study, characterized by 19 health status where all of the defibrillator cohort had an average waking wearing compliance  $\geq$ 20 than 0.63 (Figure 4).

Each participant had a profound impact on their waking and mass wearing compliance,
with men wearing having higher waking compliance than women (0.66 vs. 0.57) and retired

1 participants having higher waking compliance than those that worked outside the home (0.61 vs.)2 0.56). However, it appears that individual decisions determined the participant's wearing 3 compliance level more than general participant characteristics because the average values ranged 4 from 0.33 to 0.93. The almost significant participant-mass wearing compliance interaction term 5 also confirmed that participants tended to wear the sampling vest when exposed to elevated PM 6 concentrations. Common participant decisions that caused poor wearing compliance and biased 7 exposure levels included leaving the vest in another room while inside the house, leaving the vest 8 inside when outside of the home, and leaving the vest inside the car after arriving at their 9 destination. Such protocol violations could have caused positive or negative biases in exposure 10 levels covering several orders of magnitude. 11 Closer examination of the data in Table 1 shows the 26 participants fell into four groups. 12 Two groups showed either continual increase (6 participants) or decrease (4 participants) in 13 wearing compliance. The other two groups had either stable wearing compliance with less than 14  $\pm 0.07$  variation in the average during the study (6 participants), or showed a cyclical

15 increase/decrease pattern between seasons (10 participants). Participants cited numerous reasons

16 for not wearing the sampling vest used in the study. Personal comfort was one common reason.

17 Another explanation was embarrassment. Some participants felt embarrassed by the questions

18 and stares received while wearing the vest in public. Sometimes an employer would not allow

19 the vest to be worn at work. Other reasons were also cited.

The concept of mass wearing compliance should identify whether a participant is wearing the personal exposure monitor according to study protocols when their exposure to PM or other pollutants occurs. A fully waking wearing compliant participant will also be mass wearing

1	compliant at all PM concentration levels. If the minimum mass concentration is $10 : g/m^3$ or
2	higher, the lowest mass wearing compliance is the same as waking wearing compliance. It is also
3	true that a participant may be poorly waking wearing compliant, yet be wearing the sampler
4	during every significant PM exposure, whether by choice or by chance. Measured concentrations
5	of 100 :g/m <sup>3</sup> and above are almost always associated with proximity to a PM source (Wallace et
6	al., 2006). As a result, mass wearing compliance at $100 : g/m^3$ or higher is usually 1.0.
7	The maximum, 75%, median, and 25% mass wearing compliance values of the
8	distributions increased steadily with increasing concentration thresholds. Mass wearing
9	compliance quartiles for each concentration threshold exceeded the waking wearing compliance
10	only for concentrations above $30 : g/m^3$ . This suggests that the highest values of personal
11	concentration occurred during waking hours and that the participants were present. Comparison
12	of each participant's nephelometer concentration traces with their time-activity diaries for
13	potential PM generating activities such as cooking confirmed this conclusion (Rea et al., 2001;
14	Wallace et al., 2006).
15	Quantitative assessment of personal exposure monitor wearing compliance should be
16	more useful than evaluation of recruitment and retention efforts or exploring sociological
17	differences between participants. One goal of personal sampler wearing compliance monitoring
18	is reducing exposure misclassification which results from noncompliant personal samples
19	providing unrepresentative exposure data. Such exposure estimates do not represent the
20	participant's true exposure and weaken the statistical relationship between exposure and any
21	health effect determination. Zhao et al. (2007) used monitor wearing compliance monitoring to
22	arbitrarily set a minimum threshold of 75% waking wearing compliance for defining personal

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samples as representative of the participant's exposure. Rodes et al. (2010) and Brook et al. (2010) used a slightly lower waking wearing compliance value (60%) as being acceptable to increase the sample size included in their statistical analysis.

4 Figure 5 plots the weekly average personal-to-indoor PM<sub>2.5</sub> ratio for all participants 5 across all four seasons as a means to develop a minimum compliance threshold. The scatter in 6 the data might represent poor personal monitor wearing compliance. Other explanations might be 7 concentration differences between personal and indoor monitors due to proximity to the source 8 (Wallace et al., 2006), and significant exposures in other microenvironments. Initial analysis of 9 all data did not provide a statistically significant linear regression (p-value = 0.14). Removal of 10 the eight data with the lowest waking wearing compliance (hollow symbols) was necessary 11 before the remaining data (filled symbols) showed a statistically significant regression (p-value = 12 0.018). This analysis suggested a minimum waking wearing compliance threshold of 0.4 could be considered representative of the participant's exposure. This value is less than the value of 0.6 13 14 suggested by Rodes et al. (2010) and necessary for a statistically significant relationship between 15 PM<sub>2.5</sub> exposure and cardiovascular effects (Brook et al., 2011) in the DEARS cohort. A plausible 16 explanation for the difference is that DEARS enrolled a general population cohort while this 17 cohort consisted of health compromised senior citizens. If a minimum, cohort specific threshold 18 can be established, it becomes possible to weight personal exposure concentrations to provide an 19 estimate of what the participant's exposure might have been with perfect waking compliance. 20 Although not conducted in this analysis because all data were not available, the determination of 21 the minimum waking wearing compliance threshold should consider time-activity diary and 22 auestionnaire information that identify time spent in various microenvironments and participant

2 exposure data collected for health studies and therefore reduce exposure misclassification. 3 Conclusions 4 This paper presented a quantitative examination of personal exposure protocol 5 compliance. Waking wearing and mass wearing compliance were established. Wearing 6 compliance varied between participants. Differences in wearing compliance between cohorts of 7 different health status were not statistically significant. Participant fatigue with personal 8 exposure monitor wearing protocols over the longitudinal study was not evident. 9 One area of improvement is development of automated methods for calculating 10 compliance from activity sensor and other data. Application of signal processing algorithms to 11 combine activity sensor, temperature, and real-time PM concentration data should be explored. 12 Real-time signal processing of accelerometer and nephelometer data could also provide an 13 estimate of inhaled dose when calibrated for specific individuals; the result being a robust 14 clinical tool for identifying exposure events that trigger acute respiratory attacks. 15 Compliance estimations have potential value in significantly reducing exposure 16 misclassification. A wearing compliance threshold will allow estimation of a participant's 17 exposure assuming perfect protocol compliance, allow accurate identification of the most 18 exposed portion of the population, and strengthen the statistical relationship between exposure 19 and adverse health outcome. We suggest a combination of personal to indoor ratios and 20 questionnaire data be used to develop a minimum waking wearing compliance threshold. For this 21 cohort, a threshold of 0.4 was representative of the participant's exposure. However, compliance 22 thresholds are most likely cohort specific and need to be determined for each research study.

activities. This approach has the potential to be of value in determining the amount of useable

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10	
11	References
12	Adgate J.L., Ramachandran G., Pratt G.C., et al., 2002. Spatial and temporal variability in
13	outdoor, indoor, and personal PM2.5 exposure. Atmospheric Environment 36, 3255-3265.
14	
15	Brook, R., Bard, R., Burnett, R., Shin, H., Vette, A., Croghan, C., Stevens, C., Phillips, M.,
16	Rodes, C., Thornburg, J., Williams, R. 2011. The associations between daily community and
17	personal fine particulate matter levels with blood pressure and vascular function among non-
18	smoking adults. Journal of Occupational and Environmental Medicine 68:224-230.
19	
20	Brook, R., Shin, H., Bard, R., Burnett, R., Vette, A., Croghan, C., Thornburg, J., Rodes, C.,
21	Williams, R. 2011. Exploration of the rapid effects of personal fine particulate matter exposure

1	on arterial hemodynamics and vascular function during the same day. Environmental Health
2	Perspectives 119:688-694.
3	
4	Delfino, R.J., Quintana, P.J.E., Floro, J., Gastañaga, V.M., Samimi, B.S., Kleinman, M.T., Liu,
5	LJ.S., Bufalino, C., Wu, CF., and McLaren, C.E. 2004. Association of $FEV_1$ in asthmatic
6	children with personal and microenvironmental exposure to airborne particulate material.
7	Environmental Health Perspectives 112:932–941.
8	
9	Delfino, R.J., Staimer, N., Gillen, D., Tjoa, T., Sioutas, C., Fung, K., George, S.C., and
10	Kleinman, M.T. 2006. Personal and ambient air pollution is associated with increased exhaled
11	nitric oxide in children with asthma. Environmental Health Perspectives 114:1736–1743.
12	
13	Dockery, D., Pope III, C.A., Xu, X., Spengler, J.D., Ware, J.H., Fay, M.E., Ferris, B.J., Speizer,
14	F.E., 1993. An association between air pollution and mortality in 6 US cities. The New England
15	Journal of Medicine 329: 1753–1759.
16	
17	Ebelt, S., Petkau, A.J., Vedal, S., Fisher, T.V., and Brauer, M. 2000. Exposure of Chronic
18	Obstructive Pulmonary Disease Patients to Particulate Matter: Relationships between Personal
19	and Ambient Air Concentrations. J. Air & Waste Management Association. 50:1081-1094.
20	
21	Howard-Reed, C., Rea, A.W., Zufall, M.J., Burke, J.M., Williams, R.W., Suggs, J.C. Sheldon,
22	L.S., Walsh, D., and Kwok, R. (2000). Use of a continuous nephelometer to measure personal

1	exposure to particles during the U.S. Environmental Protection Agency Baltimore and Fresno
2	panel studies. J. Air Waste Manage. Assoc. 50:1125-1132.
3	
4	Janssen N.A.H., Hoek G., Brunekreef B., et al., 1998. Personal sampling of particles in Adults:
5	Relation among Personal, Indoor, and Outdoor Air Concentrations. Am. J. Epidemiol. 147, 537-
6	547.
7	
8	Lawless, P.A., U.S. Patent 6,502,469B2, 2003.
9	
10	Liu, L-J, Box, M., Kalman, D., Kaufman, J., Koenig, J., Larson, T., Lumley, T., Sheppard, L.,
11	Wallace, L. 2003. Exposure assessment of particulate matter for susceptible population in
12	Seattle. Environmental Health Perspectives. 111:909-918.
13	
14	Liu, W., Zhang, J., Zhang, L., Turpin, B., Weisel, C., Morandi, M., Stock, T., Colome, S. Korn,
15	L. 2006. Estimating contributions of indoor and outdoor sources to indoor carbonyl
16	concentrations in three urban areas of the United States. Atmos. Environ., 40:2202-2214.
17	
18	Liu, W., Zhang, J., Korn, L., Zhang, L., Weisel, C.P., Turpin, B.J., Morandi, M.T., Stock, T.S.,
19	and Colome, S. 2007 Predicting personal exposure to airborne carbonyls using residential
20	measurements and time/activity data. Atmos. Environ., 41:5280-5288.
21	

22 McBride, S., Williams, R., Creason, J. 2007. Bayesian hierarchical modeling of personal

1 exposure to Particulate Matter. Atmospheric Environment 41:6143-6155.

3	Pellizzari, E., P. Lioy, J. Quackenboss, R. Whitmore, A. Clayton, N. Freeman, J. Waldman, K.
4	Thomas, C. Rodes, and T. Wilcosky. 1995. Population-based exposure measurements in EPA
5	Region 5: A Phase I field study in support of the National Human Exposure Assessment Survey.
6	J. Environ. Epi 5(3):327–358.
7	Rea A.W., Zufall M.J., Williams R.W., Sheldon L., and Howard-Reed C. 2001. The influence of
8	human activity patterns on personal PM exposure: a comparative analysis of filter-based and
9	continuous particle measurements. Journal Air Waste Management Association. 51:1271-1279.
10	
11	Rodes, C.E. and Thornburg, J. "Breathing Zone Exposure Assessment" in Aerosols Handbook:
12	Measurement, Dosimetry, and Health Effects. Eds: Ruzer, L.S., Harley, N.H., CRC Press, Boca
13	Raton, FL, 2004.
14	
15	Rodes, C.E., Lawless, P.A., Evans, G.F., Sheldon, L.S., Williams, R.W., Vette, A.F., Creason,
16	J.P., and Walsh, D. 2001. The relationships between personal PM exposures for elderly
17	populations and indoor and outdoor concentrations for three retirement center scenarios. Journal
18	Exposure Analysis and Environmental Epidemiology. 11:103-115.
19	

1	Rodes, C., Lawless, P., Thornburg, J., Croghan, C., Vette, A., Williams, R. 2010. DEARS
2	particulate matter relationships for personal, indoor, outdoor, and central site settings for a
3	general population population. Atmospheric Environment 44:1386-1399.
4	
5	Schwartz, J. (2003) Daily deaths associated with air pollution in six US cities and short-term
6	mortality displacement in Boston. In: Revised analyses of time-series studies of air pollution and
7	health. Special report. Boston, MA: Health Effects Institute; pp. 219-226. Available:
8	http://www.healtheffects.org/Pubs/TimeSeries.pdf [18 October, 2004].
9	
10	Thornburg, J., Rodes, C.E., Lawless, P.A., Stevens, C.D., and Williams, R.W. 2004. A pilot
11	study of the influence of residential HAC duty cycle on indoor air quality. Atm. Environ.
12	38:1567-1577.
13	
14	Turpin BJ, Weisel CP, Morandi M, Colome S, Stock T, Eisenreich S, Buckley B., 2007.
15	Relationships of Indoor, Outdoor, and Personal Air (RIOPA): part II. Analyses of concentrations
16	of particulate matter species. Res Rep Health Eff Inst. 2007 Aug;(130 Pt 2):1-77; discussion 79-
17	92.
18	
19	Wallace, L. and Williams, R. 2005. Use of personal-indoor-outdoor sulfur concentrations to
20	estimate the infiltration factor, outdoor exposure factor, penetration coefficient, and deposition
21	rate for individual homes. Environmental Science and Technology, 39, 1707-1714.
22	

1	Wallace, L., Williams, R., Rea, A., Croghan, C. 2006. Continuous week long measurements of
2	personal exposures and indoor concentrations of fine particles for 37 health-impaired North
3	Carolina residents for up to four seasons. Atmospheric Environment, 40:399-414.
4	
5	Wallace, W., Williams, R., Suggs, J., Jones, P. Estimating Contributions of Outdoor Fine
6	Particles to Indoor Concentrations and Personal Exposures: Effects of Household Characteristics
7	and Personal Activities. ORD Report (APM 214).EPA/600/R-023. March 2006. Washington,
8	DC.
9	
10	Williams, R., J. Suggs, J. Creason, C. Rodes, P. Lawless, R. Kwok, R. Zweidinger, and L.
11	Sheldon. 2000a. The 1998 Baltimore Particulate Matter Epidemiology-Exposure Study: Part 1.
12	Comparison of residential indoor, outdoor, and ambient particulate matter concentrations.
13	Journal Exposure Analysis and Environmental Epidemiology. 10:518-532.
14	
15	Williams, R., Suggs, J. Rea, A., Leovic, K., Vette, A., Croghan, C., Sheldon, L. Rodes, C.,
16	Thornburg, J., Ejire, A., Herbst, M., and Sanders, W., Jr. 2003a. The Research Triangle Park
17	particulate matter panel study: PM mass concentration relationships. Atmospheric Environment
18	37: 5349–5363.
19	
20	Williams, R., Suggs, J., Rea, A., Sheldon, L. Rodes, C., and Thornburg, J. 2003b. The Research
21	Triangle Park particulate matter panel study: modeling ambient source contribution to personal

and residential PM mass concentrations. *Atmospheric Environment* 37: 5365–5378.

2	Williams, R., Rea, A., Vette, A., Croghan C., Whitaker, D., Wilson, H., Stevens, C., McDow, S.,
3	Burke, J., Fortmann, R., Sheldon, L., Thornburg, J., Phillips, M., Lawless, P., Rodes, C.,
4	Daughtrey, H. 2009. The design and field implementation of the Detroit Exposure and Aerosol
5	Research Study (DEARS). Journal of Exposure Science and Environmental Epidemiology, 19:
6	643-659.
7	
8	Zanobetti, A.; Schwartz, J. (2003) Airborne particles and hospital admissions for heart and lung
9	disease. In: Revised analyses of time-series studies of air pollution and health. Special report.
10	Boston, MA: Health Effects Institute; pp. 241-248. Available:
11	http://www.healtheffects.org/Pubs/TimeSeries.pdf [18 October, 2004].
12	
13	Zhao, W., Hopke, P.K., Gelfand, E.W., and Rabinovitch, R. 2007. "Use of an expanded receptor
14	model for personal exposure analysis in schoolchildren with asthma." Atmospheric Environment
15	41: 4084–4096.
16	
17	
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19	
20	
21	
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Figure 1. Example of data logger and MIE data traces superimposed by the Visual Basic program for waking and mass compliance determination. The analyst uses the activity signal (top panel), data logger temperature (second panel), the MIE concentration trace (third panel) and MIE temperature (fourth panel) to decide whether the sampler was being worn at any time. Waking wearing compliant or non-compliant intervals identified by the analyst are marked. The time period when the participant is asleep is not included in the waking wearing compliance calculation.

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9 Figure 2. Waking and mass compliance distributions across all participants and all seasons.
 10 Quartiles, minimum, and maximum values are shown.

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12 Figure 3. Waking and mass compliance distributions by cohort. The hypertensive cohort

- compliance distribution trended lower, but the difference was not statistically significant.
   Quartiles, minimum, and maximum values are shown.
- 15

16 Figure 4. Four-season average, maximum, and minimum waking compliance values by

participant cohort (HT = hypertensive, CD = cardiac defibrillator), gender (F = female, M

18 = male), and employment status (E = Employed, R = retired).

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20 Figure 5. Personal-Indoor PM2.5 ratio as a function of participant waking compliance.

21 Hollow symbols represent data omitted from the linear regression analysis to identify the

22 minimum threshold of 0.4 that identifies representative personal exposure data.

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# Figure 1.



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- 3 4 5 6 7 8 9 10 11 12 13 14 15







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- 2 Table 1. Seasonal average waking compliance for each participant, identified by cohort
- 3 (HT = hypertensive, CD = cardiac defibrillator), gender, and employment status. Results
- 4 are the average of the values calculated by the three analysts.
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- 6 Table 2. Variability in the waking and mass compliance measurements across three
- 7 analysts as represented by the coefficient of variation (CV). Values are the grand average
- 8 and average standard deviation across all participants and seasons.
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10 Table 3. General linear model results from two analyses. Model 1 examined effect of

- 11 cohort, gender, occupation, season, and PM concentration range on compliance. Model 2
- 12 replaced cohort, gender, and occupation with individual participants (ID) and added the
- 13 interaction terms.
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1 2 Table 1.

Cohort	Gender	Occupation	Summer	Fall	Winter	Spring	Average
HT	Female	Retired	0.69	0.90	0.93	0.70	0.80
HT	Female	Retired	0.51	0.22	0.51	0.69	0.48
HT	Female	Retired	0.50	0.46	0.54	0.44	0.48
HT	Female	Employed	0.41	0.42	0.57	0.54	0.48
HT	Male	Employed	0.43	0.65	0.59	0.63	0.58
HT	Female	Retired	0.50	0.59	0.43	0.60	0.53
HT	Female	Employed	0.44	0.49	0.53	0.43	0.47
HT	Female	Employed	0.54	0.51	0.09	0.50	0.41
HT	Female	Retired	0.61	0.41	0.35	0.56	0.48
HT	Female	Employed	0.45	0.56	0.05	0.51	0.39
HT	Female	Retired	0.48	0.61	0.60	0.53	0.56
HT	Female	Retired	0.58	0.60	0.65	0.49	0.58
HT	Female	Employed	0.66	0.61	0.76	0.68	0.67
HT	Female	Employed	0.67	0.46	0.60	0.59	0.58
HT	Female	Retired	0.51	0.67	0.80	0.57	0.64
HT	Female	Employed	0.40	0.51	0.49	0.50	0.47
HT	Female	Employed	0.81	0.85	0.85	0.57	0.77
HT	Female	Employed	0.66	0.74	0.77	0.81	0.75
HT	Male	Retired	0.46	0.28	0.40	0.19	0.33
CD	Male	Retired	0.92	0.88	0.96	0.94	0.93
CD	Male	Retired	0.40	0.48	0.85	0.89	0.65
CD	Male	Retired	0.90	0.74	0.54	0.59	0.69
CD	Male	Retired	0.54	0.58	0.74	0.67	0.63
CD	Male	Retired	0.53	0.80	0.82	0.80	0.74
CD	Male	Retired	0.74	0.69	0.62	0.76	0.70
CD	Female	Employed	0.53	0.81	0.55	0.69	0.64

#### 1 Table 2.

		Waking	10-20	20-30	30-50	50-100	> 100
			μg/m <sup>3</sup>				
	Grand Avg	0.59	0.44	0.51	0.56	0.60	0.60
	Avg Std Dev	0.15	0.09	0.11	0.12	0.14	0.17
	CV	0.25	0.21	0.21	0.22	0.23	0.28
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#### Table 3. 1

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	Model 1	DF	Mean Square	<b>F-value</b>	p-value
	Cohort	1	0.14	0.09	0.775
	Gender	1	0.28	6.32	0.012
	Occupation	1	0.19	4.29	0.039
	Season	3	0.02	0.50	0.683
	Conc range	5	0.41	9.45	< 0.0001
	Model 2	DF	Mean Square	<b>F-value</b>	p-value
	ID	25	0.52	44.28	<0.0001
	Season	3	0.02	1.87	0.1348
	Conc range	5	0.41	35.33	< 0.0001
	ID*Season	125	0.01	1.23	<0.0001
	ID*Conc range	75	0.11	9.45	0.0676
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