Informal Electronic Waste Recovery Workers in Ghana: The Tasks They Do, the Air They Breathe, and the Health of Their Lungs

by

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Dedication

This dissertation is dedicated to the women, men and children around the globe that work to survive. And, to those that work to help others survive while working.

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This work would not be possible without the effort, patience and trust of the Agbogbloshie e-waste workers. I want to thank them for welcoming us into their community and teaching us about their lives. I hope that this research can both represent their work and advocate for their health and safety.

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Preface

Chapter 2 (*Derivation of Time-Activity Data Using Wearable Cameras and Measures of Personal Inhalation Exposure among Workers at an Informal Electronic-Waste Recovery Site in Ghana*) has been published in Annals of Work Exposures and Health. The full list of authors is: Zoey Laskaris, Chad Milando, Stuart A. Batterman, Bhramar Mukherjee, Niladri Basu, Marie S. O'Neill, Thomas G. Robins and Julius N. Fobil.

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Abstract

Global evidence of abhorrent work conditions and environmental pollution from informal electronic-waste (e-waste) recovery in low- and middle-income countries has raised substantial concern. Air pollution from burning e-waste to recover valuable metals is particularly pressing as it is inhaled by unprotected workers and surrounding communities. Existing evidence of respiratory health effects associated with occupational exposure to airborne pollutants among e-waste workers is limited to area samples and self-reported data on respiratory symptoms, creating barriers to the design of risk-mitigating strategies. Using data from the “West Africa-Michigan CHARTER II for GEOHealth” study, this dissertation evaluates personal, task-specific inhalation exposure to particulate matter (PM) air pollution and respiratory health among informal e-waste recovery workers in Ghana.

In Aim 1, we derived task-specific concentrations to personal PM (sizes $\leq$ 2.5 ($PM_{2.5}$) and 2.5-10 ($PM_{2.5-10}$) µm in aerodynamic diameter) using time-lapse images from wearable cameras, combined with continuous and contemporaneous measures of inhalation exposure to size-specific PM. The average personal $PM_{2.5}$ concentration among workers (81 µg m^{-3}) was over three times greater than the World Health Organization’s air quality guideline for $PM_{2.5}$ (24-hour mean: 25 µg m^{-3}). The highest mean personal $PM_{2.5}$ exposures occurring during burning activities (203 µg m^{-3}), driven by short-term (5-minute), peak exposures, followed by dismantling (89 µg m^{-3}) and sorting (83 µg m^{-3}). High concentrations of personal $PM_{2.5}$ also occurred during non-work related activities (i.e., eating and drinking).

In Aim 2, we used the task-specific personal PM concentrations to estimate relative levels of exposure across work activities using linear mixed models and examined effect modification by wind conditions. Burning e-waste and bicycling were associated with the largest increases in adjusted personal $PM_{2.5}$ and $PM_{2.5-10}$, respectively, in comparison to levels when workers

performed non-work-related activities. Evidence suggested that smoke from e-waste burn-pits contributes to exposure among down-wind workers located in the plume's trajectory.

In Aim 3, we examined the association between cross-shift changes in pulmonary function and concomitant personal PM exposure (sizes <1 (PM_1) µm in aerodynamic diameter, $PM_{2.5}$ and $PM_{2.5-10}$) among 73 e-waste workers and a comparison population (n = 47). Although personal PM concentrations (all sizes) among e-waste workers were twice as high as those among the reference population, reductions in pulmonary function were not associated with increasing concentrations of personal PM in either study group. Possible explanations for these findings include: challenges in measuring baseline pulmonary function among e-waste workers who live on-site; shift durations that were too short to capture an effect; the lack of an inception cohort; and, potential selection bias due to the "healthy worker" effect.

Personal PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ concentration levels from e-waste activities considerably exceed health-based recommendations. Innovative, low-cost technologies, designed in part by the workers themselves, which eliminate the need to burn e-waste, is essential to improve air quality for the workers and communities living nearby. The lack of strong evidence demonstrating an association between PM from e-waste recovery and respiratory health effects in this sample does not preclude our responsibility to protect workers and the community by taking anticipatory actions.

1 Chapter 1: Background

1.1 Informal Electronic-Waste Recovery

Electronics are at the forefront of modern culture, technological and economic growth. The number of electronic devices owned by an individual is a marker of their economic status and on a larger scale, a country's gross domestic product (GDP)[1]. Electronic and electrical equipment that is disposed of "without intent for further use"[2] is considered waste or "e-waste". The amount of e-waste generated around the globe is expected to increase with rising economies in Latin America and Eastern Europe, new products and shorter lifespans[1]. Global estimates of annual e-waste production exceed 40 million tons[3] and have an expected annual growth rate of 4 to 5 percent[2,4]. Despite increased generation, we do not have an efficient, safe and sustainable infrastructure for its disposal.

Electronic and electrical equipment is comprised of numerous products falling into six categories: heating and cooling devices, lamps, screens, large household appliances (e.g. refrigerators, washing machines), information and communications technology equipment (e.g. PC, monitor, laptop, phone), and consumer electronics (e.g. television, lighting, microwaves)[1]. These products contain both valuable and hazardous components. Valuable components of e-waste include precious, rare and semi-valuable metals, plastics, and reusable parts[2]. In 2014, the gold (Au) content in e-waste was estimated to be 300 tons [2]. This is worth approximately 11.2 billion U.S. dollars and equivalent to 11% of the gold mined in the preceding year[2]. The hazardous components of e-waste primarily include metals (e.g. lead (Pb), cadmium (Cd), chromium (Cr)) and persistent organic chemicals (POPs), (e.g. polychlorinated biphyenyls (PCBs), and flame retardants) that are persistent in the environment and can adversely affect vital organs and the central nervous system[2,5].

The consequences of unmanaged disposal of e-waste include economic loss in materials, environmental degradation and adverse human health effects[2]. A wealth of research aiming to track the flow of e-waste from twenty-eight European Union countries plus Norway and Switzerland found that of the 9.45 million tons generated in 2012, only 3.3 million tons were officially reported as collected and recycled[6]. The rest was either unaccounted for (3.2 million tons), collected under non-compliant conditions (2.2 million tons) or improperly disposed of into municipal waste streams (750,000 tons)[6]. It is widely acknowledged that unaccounted for e-waste is either scavenged for parts, informally processed or exported without proper documentation[6,7]. This trend in poor management of e-waste also exists in North America and Australia among other wealthier regions[2]. According to the United States Environmental Protection Agency (EPA), only 15% of the total e-waste generated in the US in 2012 was collected and officially documented[2]. The cost of compliance with existing regulations on proper disposal of e-waste's hazardous components (e.g. cathode ray tubes containing lead from old televisions) may outweigh the economic and environmental incentives for recovering its value[1,6,7]. One way of avoiding these costs is to ship undocumented e-waste to low and middle income countries (LMICs) in Western Africa and Asia that have weak to no regulatory enforcement and a demand for cheap electronics[2,8].

The Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal is a global treaty initiated in 1992 that banned the largely unethical trade of hazardous materials including e-waste[9]. However, e-waste continues to flow illegally across oceans in shipping containers disguised as donations or in a mix of end of life and obsolete products. Busy ports in Ghana, Nigeria, China, India, Thailand, and Mexico are known to import e-waste containing containers yet precise descriptive statistics on the amounts are hard to produce considering its elusive market[10]. Undocumented e-waste exports are estimated to include 70% of functioning or end-of-life products and 30% true waste[6]. Once e-waste crosses the border it is either collected by a "formal" public or private collection agency or, more frequently, by a "scavenger" who keeps it or sells the collected e-waste to an informal recycler[2,8]. In Ghana, for example, an estimated 30 tons (0.2%) of its annual e-waste collection was processed in a formal facility[8]. An estimated 171,000 tons were processed by informal recyclers[8].

The International Labour Organization (ILO) defines informal sector as "the production and employment that takes place in unincorporated small or unregistered enterprises" and informal employment as “employment without legal or social protection- both inside and outside the informal sector”[11–13]. An informal e-waste recovery sector is defined by its use of rudimentary dismantling techniques, open burning, dangerous working conditions and vast environmental degradation[14]. Common methods used to recover valuable e-waste components in an informal setting include dismantling, burning, shredding, “cooking” or melting, and leaching[15,16]. Dismantling e-waste is primarily performed using a hammer and chisel. The e-waste is repeatedly chipped at and broken apart in an attempt to expose the valuable components from their non-valuable casings and coatings[7,8,17]. Beyond dismantling, the two primary metallurgical techniques used to recover valuable metals from e-waste use either heat or chemical washes[18]. Heat based treatments, such as burning, smelting and roasting, are used to recover semi-precious metals and alloys[18]. Large surface fires are ignited by workers using available materials as accelerants (e.g. tires, Styrofoam, coconut shells) until the metal scraps are revealed and can be retrieved from within the ash[7,8,17]. Alternatively, acid/alkali leaching techniques that use chemical washes are used to recover precious and rare earth metals (e.g. gold, silver, palladium and platinum) from printed circuit boards[18]. Both heat and chemical treatments performed without proper control equipment are responsible for the release of toxic emissions in the form of particulate matter (PM), gases and liquid waste[18]. Chemical methods are commonly observed at e-waste sites in China and India[16,19]. Using these rudimentary methods, the full value of e-waste is often lost. Recyclers in the informal sector primarily recover copper (Cu), aluminum (Al) and iron (Fe), tin (Sn) and brass (alloy of Cu and zinc (Zn)).

1.2 Informal e-waste recovery at Ghana’s Largest E-waste Site, Agbogbloshie

The most active informal e-waste site in Ghana, Agbogbloshie, is located less than 1km from the capital city’s central business district. The primary recovery methods used at Agbogbloshie include burning and manually processing e-waste (i.e., dismantling, pounding, shredding, and sorting). Studies of Agbogbloshie have documented unsafe levels of e-waste associated metals (toxic and essential) and organic pollutants in soil, water and biomarkers of blood and urine from workers, [16,20–22] though only one published study at Agbogbloshie has measured airborne concentrations of e-waste associated pollutants[23]. This section will summarize research documenting the evident environmental pollution from the Agbogbloshie e-waste site[20–22 24–26].

The Agbogbloshie scrap and e-waste recovery site in Ghana is an approximately 0.4 km^2 area adjacent to an informal settlement, "Old Fadama", a major food market, industrial sector and railyard. There are an estimated 4,500- 6000 e-waste and scrap workers and an estimated 80,000 people living in the near vicinity[27], although a formal enumeration of the worker population is not available. We know from existing research that the young (average 26 years), predominately male workers of Agbogbloshie differ from Accra residents with respect to culture, language and religion[8]. Most are internal migrants from Northern Ghana, Muslim with low income and poor education[27]. After leaving a life of primarily farming, they arrive in Accra with few alternative employment opportunities[8]. Workers tend to stay at the Agbogbloshie e-waste site for approximately 10 years or less[8]. Income from e-waste work tends to vary on a daily basis and by primary job-type; Workers have reported earning <10 Ghana cedi (GHS) to over 40 GHS in a day (5 GHS is equivalent to approximately 5 USD)[25,28,29]. The primary languages spoken among e-waste workers are Dagbani (local language of Northern region), Hausa (origin in Nigeria), Twi (local language of Accra) and English.

Metals: Metal concentrations sampled at Agbogbloshie that often exceed industrial standards of permissible exposure include: Pb, Cr, Cd, As, Zn, Cu, Sn, manganese (Mn) and mercury (Hg)[30–32]. Cu and Fe, metals that are essential for the body's activities, but harmful in excess, are cited as having some of the highest concentrations in sampled soil mixtures (289 mg/kg and 222mg/g respectively) at Agbogbloshie[33]. Pb is the most commonly cited heavy metal exposure associated with the dangers of e-waste recycling due to its well-known neurotoxic qualities[5,34]. It is also well known that children and adults play and live on and near the e-waste site raising additional concern. In 2011, Caravanos *et al.* analyzed 100 surface soil samples collected from around the Agbogbloshie work site; samples were found to have Pb concentrations ranging from 134 part per million (ppm) to 18,125 PPM[23]. The United States EPA standard for lead in soil is 400 ppm in non-play areas and 1200 ppm in areas where children play due to their high vulnerability to the negative developmental health effects of lead[34].

Organic pollutants: The plastics and casing of electronic and electrical equipment generally contain brominated fire retardants (BFRs), most typically polybrominated diphenyl ethers (PBDEs) and industrial chemicals such as PCBs. Depending on their volatility, PBDEs may attach more easily to soil (high volatility) whereas others may attach more easily to air and dust. Akortia *et al.* measured PBDE congeners in soil samples at Agbogbloshie that ranged from 15.6 to 96.8 ng/g[33]. In this same study, however, the estimated hazard quotient (HQ) of noncancerous toxic risk due to ingestion from PBDEs in soil for adults and children were below one indicating "minimal health risk" from PBDE exposure in the e-waste vicinity. The estimated HQ for children at the 95th percentile of exposure, however, bordered 1 for two PBDE congeners (0.91 and 0.95) indicating a potential noncancerous health risk. Inhalation may be an alternative route of human exposure that is unmeasured here[33]. Wittsiepe *et al.* measured levels of PCBs in whole blood from e-waste workers (n=39) and a reference population (n=19)[25]. Interestingly, the study revealed higher concentrations of PCBs among the controls. The authors suspect that bioaccumulation of PCBs in the food chain, particularly in fish, is the main contributor to high background levels[25]. This study sheds light on a challenge in characterizing exposures and potential health effects of e-waste associated pollution – the lack of robust background levels of e-waste pollutants in Ghanaian populations.

Air quality: Airborne pollutants at Agbogbloshie are a product of burning e-waste and other materials at low-temperatures in an unenclosed environment with non-traditional fuel sources (e.g. tires). However, dismantling, shredding, or pounding e-waste, particularly cathode ray tubes, lightbulbs, thermostats or printed circuit boards, can also generate airborne pollutants with high toxicity[35]. Emissions from electronic and electrical equipment burning and incomplete combustion include polychlorinated dibenzo-dioxins/furans (PCDD/Fs), polycyclic aromatic hydrocarbons (PAHs), carbon-monoxide, carbon, nitrogen-oxides, sulfur-dioxide and formaldehyde[16]. These pollutants can exist in the air as a gas, vapor, liquid or a solid. Dioxins, furans, PCBs, some PAHs and some BFRs are POPs due to their ability to travel over long distances and bio-accumulate in the environment by maintaining their structure over time.

Organic chemicals associated with e-waste burning practices have been measured in soil and in urine samples from e-waste workers at Agbogbloshie. The highest concentrations of

PCDD/Fs were found in soil sampled near the e-waste burning site[10,32]. This may in part be because dioxin can easily form from burning copper wiring covered in Polyvinyl chloride (PVC) plastics, a common activity at Agbogbloshie. Both PVC and copper are catalysts for dioxin formation[16]. Agbogbloshie e-waste workers were found to have higher levels of PCDD/Fs and PCBs in blood in comparison with a reference population[25]. High occupational exposures to PCDD/Fs and dioxin-like PCBs are known to cause chloracne, liver problems, elevated blood lipids and in some cases cancer[36,37]. Measures of PAH metabolites measured in urine samples among e-waste workers were found to be significantly higher than levels measured in a control population[26]. PAHs are known and probable human carcinogens causing cancer of the lung, skin or bladder[38].

There are very few direct air quality measures from near the Agbogbloshie e-waste site and only one study measuring personal inhalation risk. Caravanos *et al.* characterized ambient air (down-wind and upwind, N=2) and worker breathing zones for heavy metals (N=5 workers)[23]. Of the results above the detectable limit, the study found levels of Al (5.5 – 6.5 mg/m^3), Cu (1.2 mg/m^3), Fe (5.6-17mg/m^3) and Pb (0.98mg/m^3) to exceed the American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Values (TLVs) of 1.0, 1.0, 5.0 and .05 mg/m^3 respectively[23]. High concentrations of Cu (1.5mg/m^3), Fe (7.8mg/m^3) and Pb (0.72µg/m^3) were also measured at the down-wind monitoring station[23]. The United States EPA standard for ambient lead concentration is 0.15 µg/m^3 for a three-month average[39]. The upwind station results were all below the detectable limit (BDL).

Hogarh et al. (2018) measured atmospheric PCB concentrations at two locations near Agbogbloshie and across sixteen other sites throughout Ghana; PCB concentrations at Agbogbloshie reached 11.1 ng m^{-3} in comparison to a median concentration of 0.48 ng m^{-3} across all other urban sites[40]. The authors concluded that burning practices at Agbogbloshie were a source of atmospheric PCBs at other site locations in Accra[40]. We can gain some additional insight on air quality in Ghana from a national survey of POPs[41]. The survey revealed high levels of heavy metals and high concentrations of polychlorinated naphthalene congeners in the southern, coastal regions of Ghana[41]. The highest concentrations of polychlorinated naphthalenes were found in Teshie, an area in Accra known to burn tires, plastics, wiring and municipal waste[41].

And lastly, in a forthcoming study, Kwarteng et al. (2020) used a combination of optical and gravimetric sampling equipment to measure area levels of $PM_{2.5}$ and PM_{10} at the Agbogbloshie e-waste site and at up- and down-wind locations[42]. Mean concentrations of $PM_{2.5}$ and PM_{10} at the Agboglohise e-waste site were 88 and 214, µg m-3 respectively. The authors concluded that levels of $PM_{2.5}$ and PM_{10} on the site were substantially higher than background levels. And, that elevations in $PM_{2.5}$ at the downwind location were partially due to emissions from e-waste burning, among other local sources such as burning of municipal waste and traffic.

1.3 Risk Assessment and Respiratory Health Effects due to E-waste Associated Pollutants

Large plumes of smoke from burning e-waste in open surface fires are an unfortunate and common occurrence at informal e-waste sites. At the same time, the health burden due to air pollution from e-waste recovery activities is not yet understood. Available evidence on respiratory health outcomes due to e-waste associated inhalation exposures comes from studies conducted at the Guiyu and Qingyuan e-waste sites in southern-China’s Guangdong province.

At the Guiyo e-waste area, Zheng (2013) evaluated associations between transition metals in blood, lung function and oxidative stress among school children at an e-waste site and neighboring province (19km distance) (N=470) using a cross-sectional design. The younger age (8-9) exposed school children (boys and girls) had lower forced vital capacity (FVC) than the control group ($p<0.05$) and higher concentrations of blood-nickel (bNi) and blood-manganese (bMn). However, this trend did not exist in the older age groups. The authors hypothesize that respiratory growth between ages 12 and 15 may help recover function. Indications of distressed lung function measured in vivo were also evident in the younger but not the older age groups. Without direct measures of transition metals in the air, the interpretation of the results are limited. The study did not account for multiple factors (e.g. smoking among parents, dietary sources of metals, distance from e-waste site) that may potentially confound the results.

Two additional cross-sectional studies among children living in the Guiyu e-waste area explored these questions further[43,44]. First, Zeng et al. (2016)[43] tested the relationship between heavy metals in $PM_{2.5}$ and in blood and self-reported asthma, cough, wheeze, phlegm and dyspnea. The study found that the average $PM_{2.5}$ concentrations were higher in Guiyu (54.55 $\mu g/m^3$) than in Haojiang (36.72 $\mu g/m^3$), the comparison community. Yet, metal concentrations of Pb, Ca, Cr and Mn were not consistently higher near the e-waste site than in comparison to the reference population: Pb and Ca concentrations were higher ($p<0.01$), but Cr and Mn were similar ($p<0.05$). The blood concentrations of these metals reflected this trend; bPb and bCa were higher in Guiyu while bCr and bMn were higher in the reference population. Despite bPb levels being higher in Guiyu, 66% of the exposed and 41% of the controls had bPb levels exceeding the CDC threshold limit ($\geq$5 µg/dL). Results of multiple linear and logistic regression analyses revealed that the strongest measured predictors of asthma are having a bPb $\geq$ 5µg/dL and living in a home close to the e-waste site. More specifically, children living in a home close to an e-waste site and having a bPb $\geq$ 5µg/dL had 7.21 and 9.5 times the odds of asthma respectively in comparison to those that didn't (95%CI: 1.41 to 37.01 and 1.16 to 77.49 respectively). The adjusted-odds of cough were 2.37 times higher among those living in Guiyu than in Haojiang (95%CI: 1.30-4.32). And, the adjusted odds of phlegm were 2.73 times greater among those with child contact with e-waste (95%CI: 1.57-4.74).

The subsequent cross-sectional study (Zeng et al. 2017) among children living near the Guiyu e-waste area and in the Haojiang reference community[44], tested the associations between bPb and bCd concentrations with FVC and forced expiratory volume in one second (FEV1). The study also evaluated blood parameters as a potential mediator between metal exposure and lung capacity. Mean bPb among exposed children (5.53 µg/dL) were found to be 1.37 µg/dL times higher ($p<.001$) than the reference population. BCd levels were similar among both populations. Reflective of previous findings, the associations between blood metals and lung capacity were mixed. Absolute FVC and FEV1 values for exposed boys, but not girls were significantly lower than the reference population. However, predicted values for both FEV1 and FVC across sex and population were not consistently different. Living in the exposed area remained a strong predictor of lower lung function after adjusting for age, gender, height, red blood cell distribution width (RDW), family member daily smoking, parental education level, family income level, daily outdoor play time and log-transformed bPb and log-transformed bCd.

Lastly, hemoglobin (1 g/L) decline was associated with 5 mL decrease in FVC and 4 mL decrease in FEV1, however the study did not conduct a formal mediation analysis. The authors believe that both the 2016[43] and 2017[44] studies may have been subject to confounding due to fly ash from thermal power plant exposure in Haojiang, the reference area. Fly ash may be a source of Cr and Mn exposure. A common limitation in the existing e-waste research is having an inappropriate or lack of a control population. It is challenging to identify a population with similar characteristics as those living near an e-waste but without any exposure to the numerous types of e-waste associated pollutants. Moreover, a longitudinal study among the children living in an e-waste area with repeated air quality and spirometry measure would greatly contribute to our understanding of e-waste associated respiratory health effects.

Four studies from China with direct air quality measures focused on the estimated health risks of particulate organic pollutants, specifically PAHs[45,46], organophosphate-[47], and halogenated flame retardants[48]. All four studies measured and compared levels of these organic pollutants in PM (both size-dependent and in total suspended particulate) from an e-waste and urban area. The key takeaway is that PAHs presented the greatest inhalation risk to human health in comparison to flame retardants.

Concentrations of PAHs in PM at the e-waste area (range: 4.2 - 5.0 ng/m^3) exceeded China's daily standard (2.5 ng/m^3) on the majority of sampling days[45]. PAHs were found to be particularly threatening to human health due to their tendency to bind primarily to fine and ultra-fine PM. Fine and ultrafine PM is known to deposit into the tracheobronchial and alveolar regions of the respiratory system where it can more easily pass into systemic circulation. Cancer risk (CR) was estimated using the toxic equivalency factor of benzo[a]pyrene (BaP) and a unit relative risk (UR) of 8.7x10^{-5} per ng/m^3 (based on epidemiology of coke oven workers). The incremental CR for bulk and deposition concentrations of BaP were 360 (95%CI: 195-62) and 150 (95%CI:92-230) cases per million people in the e-waste recycling zone compare to 184 (95%CI: 110-305) and 75 (95%CI: 45-120) in the urban area. An earlier study that measured PAHs in total suspended particulate (TSP) also estimated an elevated inhalation CR, however estimates may have been overestimated due to the fact that atmospheric PAH deposition and inhalation cancer risks are highly size dependent[46]. Alternatively, concentrations and estimated hazards from outdoor exposure to organo-phosphate and halogenated flame-retardants were found to be low at both the e-waste and urban sites[47,48].

The risk projections of all four of these studies[45–48] are limited to short-term sampling during only three months of the year from two fixed monitoring stations, and speculative in their approach. Additionally, there are uncertainties inherent in their model parameters. Future risk characterizations from e-waste exposures should be based on direct measures of individual inhalation exposure.

Lastly, one small cross-sectional study (Li, 2013) among adults living near an e-waste site and in an urban area in China measured organic pollutants (specifically PCBs, PBDEs, PBBs etc.) in plasma[49]. The measured health outcome was ROS, an indicator of oxidative stress and ROS generated neutrophil respiratory burst, an indicator of immune function. Oxidative stress is the biological mechanism perceived to be the link between inhalation exposure to e-waste associated pollutants and chronic lung conditions. Of all the organo-halogen pollutants measured in plasma samples, over 35 congeners, PCB concentrations differed most strongly between the exposed and reference populations. Exposed had PCB concentrations 2.2 times higher than the reference group. Similarly, the study identified PCBs to be the most likely exposure leading to oxidative stress. The authors confirmed their hypotheses with a positive association between PCB levels and ROS and an inverse association between PCB levels and ROS generated in neutrophil respiratory bursts. The study did not measure or control for a number of potential confounders such as smoking, health status and PCB exposures from other sources.

The existing evidence of e-waste associated respiratory health effects from Agbogbloshie is limited to self-reported data. Workers attribute e-waste as the source of some of their physical ailments, particularly burns, cuts, tetanus, back and chest pains, and breathing problems [29,50]. In interviews recorded by Asampong et al. (2015), workers frequently reported chest pain, respiratory infections and cough; one worker described the sensation, “When the smoke goes into you breathing becomes difficult. You feel pains in your chest and you cough. You can be doing the work in the fire and the fire can get you injured.”[50] In a separate study, Agbogbloshie e-waste workers, in comparison to a reference populations, reported higher prevalence of cough

(65% vs. 9.5%, p-value <0.001); chest pain (25.3% vs. 0%, p-value <0.001); and dizziness/ vertigo (16% vs. 0%, p<0.006) in the past four weeks prior to study recruitment[26].

Despite the breadth of research on environmental pollution from e-waste recovery practices, we do not have conclusive evidence on the acute and chronic health outcomes associated with e-waste exposures. Existing studies are cross-sectional (eliminating the possibility of generating causal epidemiologic evidence) and most rely on convenience samples without reference populations to establish exposure baselines. Substantial unmeasured confounding and limited data on measured health outcomes further weaken causal evidence. There is a particularly limited understanding on the association between respiratory health outcomes and e-waste associated air pollutants. This may be due to the challenges in measuring both airborne pollutants, specifically from the breathing zone of workers, and respiratory-related health outcomes, many of which require long-term follow-ups, among transient worker populations. With multiple sources of air pollution in LMICs, (i.e., traffic-related emissions, waste burning, and burning of BMF for cooking), measuring associations between e-waste emissions and respiratory health effects requires data on background concentration levels. Lastly, the number of pollutants, pollutant mixtures, routes of exposure, and potential adverse health outcomes make it challenging to interpret and compare findings across different studies.

1.4 Epidemiology of Particulate Matter Air Pollution

Air pollution is a combination of particulate matter and gases suspended in the air. The most common sources of air pollution are fuel combustion, traffic-related air pollution and, particularly in the developing world, household air pollution from the burning of biomass fuels (BMF) for cooking and heating[51]. Air pollution emissions include a mix of sulfur dioxide (SO2), nitrogen oxides (NOx), ozone, PM, carbon monoxide (CO), lead and other metals, black carbon, volatile organic compounds (VOCs), POPs, and formaldehyde [52–55]. PM is formed from aerosols that form in the air from suspended solid and liquid particles of varying size, shape and composition. PM contains metals, carbon, sulfates, nitrates, ammonia, sodium chloride, black carbon, PAHs and other POPs, biologicals, mineral dust and water[56]. The exact composition, toxicity and exposure characteristics of air pollution vary according to the source, fuel type, and meteorological conditions among other factors[52,53].

Exposure to airborne pollutants may occur through inhalation, ingestion of dust and particulate, and dermal absorption of gaseous organic contaminants[52,53]. In 2013, IARC established outdoor air pollution and PM in outdoor air pollution as Group 1 carcinogens[57]. Robust evidence, predominantly from data collected in North America, Europe and China, identify particulate air pollution of respirable sizes (aerodynamic diameter $\leq$ 10 µm) as a contributor to cardiovascular, respiratory and in some cases cerebrovascular morbidity and mortality[55,58–62]. The major health effects attributed to household and outdoor air pollution in Sub-Saharan Africa include acute lower respiratory infections, chronic obstructive pulmonary disorder (COPD), ischemic heart disease, stroke and lung cancer[54,56,63–66]. Those most susceptible to the health risks of air pollution are children, elderly, individuals with preexisting respiratory and cardiovascular conditions and workers exposed to chronic and elevated concentrations levels[58,62,67].

The size of PM determines how deeply it is deposited into the lungs. The coarse PM fraction has an aerodynamic diameter $\leq$10 µm and >2.5µm ($PM_{2.5\text{-}10}$). $PM_{2.5\text{-}10}$ is deposited in the upper airways. PM with a diameter of $\leq$2.5 µm ($PM_{2.5}$) is deposited deeper into the lungs where it can reach the alveoli that provide oxygenated blood to blood vessels. By reaching the lower respiratory system, $PM_{2.5}$ can pass into systemic circulation. Ultrafine PM ($PM_{0.1}$) has a diameter $\leq$ 0.1 µm. $PM_{0.1}$ can easily pass into systemic circulation and further to the liver, spleen, heart or brain[52]. $PM_{0.1}$ emissions exist in the air for a short period of time before attaching to larger suspended particles[64,68].

$PM_{2.5}$ and its constituents have been shown in *in vitro* animal and *in vivo* epidemiological studies to be associated with an increase in respiratory symptoms and hospital admissions, reduced baseline lung function and increased rate of decline, acute lower respiratory infections, asthma, chronic bronchitis, COPD, pulmonary fibrosis, cancer and mortality[53,57,62,69–71]. Emerging evidence on the association between air pollution, specifically from BMF and traffic-related air pollution, and tuberculosis (TB) incidence has produced mixed results[64].

The primary biological mechanisms driving the health effects associated with PM are oxidative stress and inflammation[53,64,70]. Particulate and gaseous pollutants can upset intracellular regulation of inflammation. PM can stimulate local inflammation by penetrating and irritating different areas of the lung's mucous membrane. Chronic inflammation may result in an airway obstructed by an over secretion of mucus and reduced lumen diameter. Reduced lumen diameter may also be the outcome of bronchial hyperreactivity (BHR); BHR is characterized by abnormalities of the airway smooth muscle cells and altered response to foreign stimuli[72]. Moreover, fine particulate and irritants can cause an inflammatory response by passing through the airways and depositing in the alveoli. Inflammation can be triggered by cytokine production and impaired alveolar macrophage viability[53,64,70]. Black carbon, a constituent of PM, is associated with inflammation mediated excessive cell production that distorts the lungs structure – a component cause of pulmonary fibrosis. Alternatively, transitional metals and particulate phase PAHs, also constituents of PM, have been shown to stimulate the production of free radicals[53,64,70]. We know about the respiratory health effects of transition metals from research among nickel welders and foundry workers[73]. Reactive oxygen species (ROS) mediated oxidative stress can result in DNA damage and cancer of the trachea, bronchioles or lungs[53]. In summary, PM itself, the characteristics of its constituents and its size are three of the main factors that determine the biological mechanism and health effects it may trigger.

1.5 Summary

There is increasing evidence of occupational, environmental and community health risks due to e-waste recovery practices at the Agbogbloshie e-waste site in Ghana and around the globe[74]. Despite substantial evidence documenting unsafe levels of e-waste associated pollutants in environmental media, body burden and risk assessments[10,16], epidemiologic evidence of acute and chronic health conditions due to occupational exposures are limited[5]. The two main recovery methods used at Agbogblohie, manual dismantling and burning, have been shown to be the most abundant and dangerous sources of e-waste associated pollutants [8,20,26,75], however existing studies have failed to detect differences in concentrations or health outcomes across job types[20,25,26,28]. Limitations in the existing data are, in part, due to the challenges associated with data collection in informal or non-traditional work settings (e.g., the lack of a clearly defined organizational structure, formal job titles, work protocols, employee records and the transient nature of the workers). In addition to, the manifold pollutants and hazards associated with e-waste recovery work combined with limited data on background levels of the same pollutants among populations living in LMICs[25,26]. Particularly limited is our understanding of respiratory health conditions among workers due to airborne pollutants from burning e-waste and other activities, such as dismantling and pounding e-waste. Measures of air quality from e-waste sites are limited to area samples[41,42] and respiratory health assessments among workers are limited to self-reported data on symptoms[17,26,29]. New research efforts must work towards generating data that can be applied to the design of risk-mitigating strategies (e.g., job-specific exposure assessments) and establishing causal evidence of e-waste associated health effects.

1.6 Specific Aims and Hypotheses

This dissertation will contribute to our understanding of occupational exposure to airborne pollutants and respiratory health effects from e-waste recovery activities. In light of the research challenges associated with data collection in informal sectors, this dissertation will also seek to improve existing methods of data collection for informal and other non-traditional job settings.

The parent study providing data for this dissertation is “The West Africa-Michigan CHARTER II for GEOHealth” (GeoHealth), based in Accra, Ghana. GeoHealth is a longitudinal occupational cohort study with four waves of data collection (2017-2018). It is the first study of informal e-waste workers with repeated measures of personal inhalation exposure to size-specific particulate matter and quantitative measures of health status from spirometry and questionnaires. The participants comprise a sample of e-waste workers (n=142) and a gender-matched local reference population (n=65).

Aim 1: To use self-reported and image-based time-activity data to characterize the type and duration of tasks performed by e-waste workers at the Agbogbloshie site.

We hypothesize that: time-activity will be defined by high variability in the duration and number of tasks performed during a work-shift; and, that the agreement between hand-written and image-based time activity data will be low.

Aim 1a: To derive task-specific breathing zone concentrations to personal $PM_{2.5}$ using image-based time-activity data combined with continuous and contemporaneous measures of personal inhalation exposure to size-specific PM among e-waste workers at the Agobogbloshie e-waste site.

We hypothesize that: participants will have personal $PM_{2.5}$ *concentrations that exceed WHO's target ambient air quality guidelines (24-hour mean* $PM_{2.5}$ *: 25 µg* m^{-3}*); and that exposures to* $PM_{2.5}$ *will be highest during burning followed by dismantling, sorting and loading e-waste recovery tasks.*

Aim 2: To compare relative levels of the concentrations of personal $PM_{2.5}$ and, additionally, $PM_{2.5-10}$, developed in Aim 1 across work activities among workers at the Agbogbloshie e-waste site.

We hypothesize that: e-waste burning activities will be associated with the largest increases in personal $PM_{2.5}$ *concentrations in comparison to non-work-related activities; and, that e-waste processing activities, including dismantling, sorting and loading, will be associated with the largest increases in* $PM_{2.5-10}$ *in comparison to non-work-related activities.*

Aim 2a: To measure the joint effects of e-waste activities and wind conditions on personal inhalation exposure to $PM_{2.5}$ *and* $PM_{2.5-10}$.

We hypothesize that personal inhalation exposure to $PM_{2.5}$ *and* $PM_{2.5-10}$ *will be highest among burners who cannot move upwind of the emission source during conditions of a meandering plume caused by low wind speeds and high variability in direction. We also* *hypothesize that personal inhalation exposure to $PM_{2.5}$ and $PM_{2.5\text{-}10}$ will be highest among dismantlers located downwind of the emission source during conditions of low plume rise caused by high wind speeds and low variability in direction.*

Aim 3: To examine the association between cross-shift changes in pulmonary function, including forced vital capacity (FVC), forced expiratory volume in one second (FEV1) and the FEV1/FVC ratio, with personal exposures to concomitant PM_1 (<1 µm), $PM_{2.5}$, and $PM_{2.5\text{-}10}$ among e-waste workers at Agbogbloshie and a reference community in Accra, Ghana.

We hypothesize that: e-waste workers in comparison to the reference community will have greater reductions in FEV1, FVC and the FEV1/FVC ratio following a work shift; and, that increases in exposure to PM1, $PM_{2.5}$ and $PM_{2.5\text{-}10}$ during the work-shift will be associated with decelerations in pulmonary function among both populations.

Aim 3a: To examine the association between cross-shift changes in pulmonary function and activities performed during the work-shift by e-waste workers at the Agbogbloshie site.

We hypothesize that burning, followed by dismantling, sorting, and loading e-waste activities, will be associated with reductions in pulmonary function in comparison to non-work-related activities.

2 Chapter 2: Derivation of Time-Activity Data Using Wearable Cameras and Measures of Personal Inhalation Exposure among Workers at an Informal Electronic-Waste Recovery Site in Ghana

2.1 Abstract

Background: Approximately two billion workers globally are employed in informal settings, which are characterized by substantial risk from hazardous exposures and varying job-tasks and schedules. Existing methods for identifying occupational hazards must be adapted for unregulated and challenging work environments. We designed and applied a method for objectively deriving time-activity patterns from wearable camera data, and matched images with continuous measurements of personal inhalation exposure to size-specific particulate matter (PM) among workers at an informal electronic-waste (e-waste) recovery site.

Methods: 142 workers at the Agbogbloshie e-waste site in Accra, Ghana, wore sampling backpacks equipped with wearable cameras and real-time particle monitors during a total of 171 shifts. Self-reported recall of time-activity (30-min resolution) was collected during end of shift interviews. Images (N=35,588) and simultaneously measured $PM_{2.5}$ were collected each minute and processed to identify activities established through worker interviews, observation and existing literature. Descriptive statistics were generated for activity types, frequencies, and associated $PM_{2.5}$ exposures. A kappa statistic measured agreement between self-reported and image-based time-activity data.

Results: Based on image-based time-activity patterns, workers primarily dismantled, sorted/loaded, burned and transported e-waste materials for metal recovery with high variability in activity duration. Image-based and self-reported time-activity had poor agreement (kappa = 0.17). Most measured exposures (90%) exceeded the World Health Organization (WHO) 24-hour ambient $PM_{2.5}$ target of 25 µg m^{-3}. The average on-site $PM_{2.5}$ was 81 µg m^{-3} (SD: 94). $PM_{2.5}$ levels were highest during burning, sorting/loading and dismantling (203, 89, 83 µg m^{-3} respectively). $PM_{2.5}$ exposure during long periods of non-work-related activities also exceeded the WHO standard in 88% of measured data.

Conclusions: In complex, informal work environments, wearable cameras can improve occupational exposure assessments and, in conjunction with monitoring equipment, identify activities associated with high exposures to workplace hazards by providing high resolution time-activity data.

2.2 Introduction

Improved methods for occupational exposure assessment can contribute to health and well-being among the world's estimated two billion informally employed workers [76]. These workers are not subject to national labor standards, and are at substantial risk of hazardous work conditions, including high levels of exposures to toxic agents with little or no social, economic or occupational protections [11,76]. The unregulated and unorganized structure of informal worksites limits data collection, establishment of linkages with adverse health effects, and design and implementation of risk-mitigating strategies.

Combining task-specific time-activity measures with task-specific concentrations enhances the ability to estimate levels of personal occupational exposure. Task-specific exposure estimates help establish exposure groups and dose-response relationships between exposures and measured health outcomes [77]. Additionally, time-activity can reveal risk factors that may affect an employee's health. In informal sectors, collection of time-use data using standard methodologies, such as written diaries, may lack the precision to detect acute exposures.

In the informal electronic waste (e-waste) recovery sector, hazardous work conditions and environmental pollution have raised considerable alarm [14]. Up- and downstream solutions are urgently needed to redesign the organizational structures that handle global e-waste [78]. Task-specific exposure information is needed to identify high risk worker groups, strengthen causal evidence of adverse health outcomes, and motivate stakeholder action and interventions.

At the Agbogbloshie informal e-waste recovery and scrapyard in Accra, Ghana, job-titles, schedules, and task protocols are unavailable, so previous studies derived exposure groups using alternate methods. Interviews revealed that most workers participated in an average of seven (maximum of nine) different jobs [20]. Workers who sorted e-waste had blood-lead 2.2 times higher than non-sorting controls, and workers who burned e-waste had urinary copper and zinc 1.7 times higher than non-burning controls [20]. No significant differences were found in elemental exposures when comparing workers across the primary job of the past six months [20]. A study on noise exposure and heart rate used 15-minute time-activity diaries, and found that activity did not significantly confound or modify the observed positive association between noise and heart rate [28]. The lack of detectable differences in exposure across self-reported primary job task or time-activity recall in these and other studies [25,26] may be due to substantial task misclassification, which may obscure critical differences in associated health risks.

Airborne pollutants, such as particulate matter of aerodynamic diameter $\leq$ 10 or <2.5 µm, PM_{10} and $PM_{2.5}$, are generated during e-waste recovery practices [10]. The health effects associated with PM_{10} and $PM_{2.5}$ exposure [60,62] may be modified by the types of tasks workers perform. There are no published comprehensive evaluations of general or task-specific personal inhalation exposure among informal e-waste workers. One small-scale study (n=5) sampled the breathing zone of informal e-waste recovery workers at Agbogbloshie and found levels of aluminum, copper, lead, iron and zinc that exceeded workplace limits (Caravanos et al., 2011). Comprehensive data could guide risk-mitigating interventions and enhance our understanding of how elevated chronic and short-term peak exposures to PM typical of other informal sector settings affect health [59].

This study aims to address the gaps in exposure assessment in informal settings by using wearable cameras and personal exposure monitoring equipment to generate task-specific exposures. We utilize an ongoing longitudinal cohort study based at the Agbogbloshie e-waste recovery site, the West Africa-Michigan CHARTER II for GEOHealth (GeoHealth-II), designed to assess environmental and occupational health hazards and overcome limitations of prior studies. Data for this study were collected among e-waste worker participants (N=142) between March 2017 and April 2018. Self-reported and image-based time-activity data are used to characterize the type and duration of tasks performed by e-waste workers on the Agbogbloshie informal site. The agreement between sources of time-activity data is quantified. Image-based time-activity is used to identify activities strongly associated with high concentrations of contemporaneously measured personal $PM_{2.5}$, i.e., burning and dismantling e-waste. The method described in this paper for using wearable cameras to derive validated and time-resolved time-activity data can be adapted for occupational settings with an urgent need to identify sources of acute exposures and other hazards.

2.3 Methods

2.3.1 Study Location and worker population

The Agbogbloshie e-waste and metal scrapyard in Ghana is a 0.5 km^2 area near Accra's central business district and adjacent to a food market, industrial sector, and informal community with a population of 79,684 (2009)[27,79]. Figure 1 provides an aerial view of Agbogbloshie. Prevailing winds are south, south-westerly. Work stations are not formalized and work- and non-work-related activities are adjoined; mosques, domiciles, food vendors, cattle and other subsistence activities are interspersed among individuals or groups performing e-waste recovery tasks.

The site is overseen by the Scrap Dealers Association (SDA). Its chair reported not knowing the number of workers on-site or if a new worker arrived in the preceding month. There are also no formal job titles or task protocols. The majority of workers who migrate to Accra from Ghana's rural Northern region seeking employment opportunities are in their twenties [8]. They are predominantly Muslim and Dagbani-speaking, thus differing from the Twi-speaking, Christian majority in Accra[8].

2.3.2 Study sample

Participant data come from the GeoHealth-II longitudinal cohort study. Data were collected during three study waves (beginning in March 2017, August 2017, and January 2018) among e-waste worker participants (N=142).

Following a public presentation on the study, workers who were willing to join the study were enrolled (N=100). More workers requested enrollment than the study had resources for. Although recruitment was planned for wave I only, new participants were enrolled at wave II (N=42), in order to replace those that were lost to follow-up between waves I and II. Follow-up visits occurred during waves II and/or III; participants were located by cell phone and with the help of seasoned workers. Of the 142 recruits, 70 completed all three waves, 35 completed two and 37 completed one.

Informed consent was obtained and questionnaires were administered by trained, local interpreters in the participants' native or preferred language: Dagbani, Hausa, Twi or English. Participants were compensated at each wave with 30 Ghana Cedis (approximately US $7, roughly an average day's wage), a T-shirt and lunch. The University of Ghana and University of Michigan Institutional Review Boards (IRB) approved the study protocols. The local chief of Agbogbloshie, and chair and vice-chair of the SDA gave permission and allowed the research team to enter the community.

2.3.3 Data Collection

A diagram depicting the stages of data collection is available in the supplementary materials (Fig S1). Wave I, II and III were aligned with the dry, rainy and Harmattan (winds coming off the desert) seasons, respectively, to achieve seasonal variation in work patterns and personal exposure.

2.3.3.1 Survey Instruments

A questionnaire administered during baseline visits included an extended section on occupational history and job tasks. In wave II only, a time-activity diary with a 30-min resolution was administered by an interpreter at the end of personal monitoring sessions (See supplementary Fig S2). Participants were asked to recall their activities from the time they started work. The diary included nine pre-selected e-waste recovery tasks identified in a prior study among Agbogbloshie e-waste workers [20].

2.3.3.2 Wearable Camera and Personal PM monitoring

Three sampling backpacks containing a wearable, time-lapse camera and personal PM inhalation exposure equipment were deployed in the morning on all days excluding Sunday. Length of sampling was set to four hours between 8:00AM and 2:00PM based on the observation that non-work activities increased in the latter half of the afternoon. Sampling duration was reduced to two hours during wave III, because of high levels of PM from Harmattan winds. Time-lapse images were collected in one minute intervals using a wide-angle GoPro

Hero4© camera mounted to the backpack's forward facing shoulder strap. Minute-by-minute PM was measured using a 5-channel optical particle counter (Aerocet 831, Met One Instruments, Inc., OR, USA), which converts counts into size-specific mass measurements (µg m-^{3}) using a proprietary algorithm. The instrument's concentration range is 0 to 1000 µg m-^{3}, beyond which particle coincidence error leads to under-reporting.

2.3.4 Deriving time-activity patterns (TAPs) from images

Two trained reviewers at the University of Michigan categorized images into activities using a data collection instrument designed on the Research Electronic Data Capture (REDCap) secure web platform (See supplementary Fig S3 for a transcript of the instrument). Reviewer identified activities could come from a single image (e.g. smoking) or a group of images depicting one sustained activity. A checklist of objects helped characterize activities (e.g. flames indicated burning). This input and the response to subsequent questions about the specific activity that automatically followed were used to create time-activity patterns (TAP) for each participant.

TAPs are continuous, detailed, and time-specific logs of all activities performed by a participant. Each TAP is comprised of a time-ordered series of "events"; an event is comprised of 1 or more consecutive images that identified a sustained work- or non-work-related activity (Figure 2). Because our focus was on detecting work-related activities, brief periods of rest and position changes ($\leq$5 min) bounded by the same identifiable activity were not recorded as separate events.

TAPs from pilot data were discussed with workers during four on-site interviews to confirm the accuracy of activity classifications. Workers described the activities from a series of images depicting all work and transportation-related activities, in addition to some images with unclear classifications. The interviews revealed a distinction in how workers and reviewers classified some activities. Workers identified a task from one sub-task; for example, what a reviewer described as "bicycle transit", a worker named "collecting" – the term used for travelling off-site (often by bi- or tricycle) to purchase or scavenge e-waste materials. Reviewers unfamiliar with a worker's intent were instructed to classify sub-activities in order to detect specific activities associated with high levels of inhalation exposure. This learned information was taken into consideration when testing agreement with worker's self-report.

The final instrument's work-related categories included burning wires, burning material other than wires, starting or igniting a fire, stripping wires, dismantling/pounding/breaking, on-/off-loading, gathering/sorting, transporting materials (off or on-site), trading/selling, weighing, repairing, and smelting (lead or aluminum) (see supplementary Table S1 for descriptions). Images which showed that the sampling backpack (including the camera and PM monitoring device) was not being worn as intended were categorized as "unusable". Images of backpack deployment and retrieval were categorized as "staging area". For more details of image processing steps and output see supplementary Table S2.

Creating an averaged database of PM and TAP

The minute-by-minute TAP database was merged with contemporaneous minute-by-minute size-specific PM levels using participant ID, date and time. Additionally, a 5-minute average database was made to reduce sampling noise associated with PM measures and a 30-min averaged database was made to test agreement with self-reported time-activity diaries. For the averaged databases, the most frequently occurring activity within each 5- or 30-minute period was selected to be representative (further coding details in supplementary Table S2). "Unusable" images were removed post-averaging if they were the dominant event for the averaged interval.

2.3.5 Statistical Analyses

The baseline questionnaire was used to describe job characteristics and task history. The image-based 1-min TAPs were used to describe the type and duration of all activities performed during waves I, II and III. To measure the agreement between self-reported and image-based time-activity, a subset of wave II diaries and 30-min TAPs were used. Unweighted kappa statistics were calculated to measure agreement beyond chance. A kappa score was calculated for time-activity designation based on eight activity categories (burning, dismantling, material movement and organization, buy-sell-weigh, repairing, smelting, other (work-related), non-work) (see supplementary Fig S2 for details on activity categories).

The 5-min TAPs were used to evaluate the capacity of image-based time-activity data to detect job tasks that were strongly predicted to have the highest concentrations of $PM_{2.5}$

inhalation exposure. Data collected during an urban fire near Agbogbloshie were excluded from the 5-min TAPs (n=695 min) and PM summaries. Descriptive statistics of $PM_{2.5}$, PM_1 (aerodynamic diameter ≤ 1 μg), $PM_{2.5-10}$ (the coarse fraction of PM calculated using the difference method), and total suspended particulate (TSP) are summarized by activity. Exposure groups based on cut-off points derived from the 25th, 50th, 75th, and 95th percentiles of $PM_{2.5}$ were used to examine the amount of time participants spent in each exposure group by activity. The non-parametric Mann-Whitney U test compared $PM_{2.5}$ concentrations in our subsample with those of the excluded "unusable" data in which participants removed their sampling backpacks. All analyses were accomplished using the statistical software R [80].

2.4 Results

Of the 142 baseline occupational questionnaires, one participant was excluded due to missing over 90% of responses, resulting in a final selection of 141 participants. Personal monitoring with images and PM levels was completed in 63 days between March 2017 and February 2018 (22, 20 and 21 days in waves I, II and III respectively) by 110 unique participants. Our final 1-min database comprised 32,439 classified images with contemporaneous PM estimates from 109 unique participants after excluding "unusable" images (n=3,149, which included all images from one participant) (see supplementary Fig S1). A unique participant completed either one (n=55), two (n=47) or all three (n=7) waves resulting in 170 partial-shift samples. The mean sampling durations per partial-shift were 210 (SD:102), 211 (SD:72) and 153 (SD:80) minutes in waves I, II and III respectively, and close to the targeted sampling duration (240 min in waves I and II and 120 min in wave III).

2.4.1 Self-reported and image-based time-activity

Participants were an average of 27 years old, over 90% were Muslims originating from the Northern region of Ghana with mostly low education and income, and over 70% earned the equivalent of less than 10 USD per day (see supplementary Table S3). 88% of participants lived on or within 1km of the e-waste site and worked 6 to 7 days a week for an average of 10 hours per day. Participants reported working at Agbogbloshie for an average of 8.6 years.

Dismantling e-waste followed by trading/selling and burning e-waste are the most commonly reported job-tasks ever and currently performed at Agbogbloshie within the sample (see supplementary Table S4). Fewer than 10% reported repairing e-waste, weighing or smelting lead batteries. "Other" jobs included mechanic and taxi driver. Almost all participants who reported performing a job in the past were still currently performing the same job. On average each participant reported having *ever* performed 3.2 jobs (range: 1-6) and *currently* performing 2.9 (range: 1-6). Survey data indicated wide differences in the percent of workers "currently" performing a job with those reporting that job as their primary job (e.g. 82 participants reported "currently" performing burning and 26 indicated that it was their "primary job over the past three months").These conditions reinforce the need for a real-time and objective method to accurately document time-activity.

Image-based results on the frequency, type and duration of activities are summarized in Table 1. Reviewers classified a total of 910 events. Each TAP included an average of 5.6 events (range: 1- 16) per participant. Event duration varied by activity (see supplementary Table S5 for details on activity-specific durations). Activity types and durations remained approximately equivalent across waves I, II and III; however, the overall number of work-related events decreased from wave I to wave III, and the number of "unusable" images increased.

Among work-related activities, representing 28% of sampling time (n = 8,806 images), dismantling (50%), sorting and loading (17%), burning (14%) and transporting materials (10%) were most common (Table 1). No participants performed smelting. "Non-work-related" activities in which participants did not appear to be actively working represented 53% (n=17,072 images) of the total sampling time. An estimated 66% of non-work related activities occurred on the e-waste site based on the presence of objects indicative of the site (e.g. e-waste materials, tools, fire), however the proportion is most likely higher. For transportation, participants primarily walked short distances (mean (SD): 16 (11) minutes) on or near the e-waste site.

2.4.2 *Agreement*

The self-reported diaries (30-min resolution) and matched 30-min TAPs used to test agreement are summarized in Table 2. This subset of wave II data covered 349 30-min intervals from 51 participant diaries (mean: 205 min/diary). The agreement was low (0.17), indicating "none to slight" agreement [81]. Sensitivity analyses examined sources of misclassification and revealed that agreement did not differ depending on the number of activities performed during the shift, but agreement improved if we ignored the time during which activities occurred. Under this scenario, the percent agreement was highest for non-work (96% agreement) and dismantling activities (40%) and lowest for buy/sell/weigh (15%) and burning (33%). In addition, participants occasionally reported performing an activity even if they were sitting near to where the activity was being performed by others. This was determined by reviewing all images for time-intervals in which a participant self-reported burning and the reviewer did not (n=6 30-min intervals). In 50% of the images (n=90) the participant was sitting in a rest-area located in proximity (approximately 10 meters) to the burning zone, but not actively burning e-waste. The remaining images showed no evidence of burning or being located near the burning zone.

2.4.3 *Personal inhalation exposure to $PM_{2.5}$*

$PM_{2.5}$ concentration estimates are summarized by activity type in Table 3 and in Figure 3. Data excluded due to "unusable" images had significantly lower mean $PM_{2.5}$ concentrations than our final sample (73 versus 81 µg m^{-3}, Mann-Whitney p-value: $p< 0.001$) (discussed further in Discussion section). Overall, the $PM_{2.5}$ arithmetic and geometric mean concentrations were 81 (SD: 93) and 60 (SD: 2.1) µg m^{-3} respectively. The mean $PM_{2.5}$ concentrations for activities believed to have been performed on-site (based on objects identified in the images) were significantly higher than those performed off-site (85 versus 72 µg m^{-3}, Mann-Whitney p-value: 0.014) despite the fact that most off-site activities included travel on major roadways. Work-related activities had the highest mean $PM_{2.5}$ concentrations (100 µg m^{-3}) as compared with transportation- and non-work-related activities. Burning activities had the highest $PM_{2.5}$ exposures of all activities (203 µg m^{-3}). The mean concentrations for sorting/loading and dismantling were approximately 56 and 60% lower than burning, but still higher than all other tasks. At the same time, median $PM_{2.5}$ concentrations between work- and non-work-related activities were largely similar; all individuals on the site, regardless of their activities, experienced poor air quality. Inhalation exposure reached the highest exposure group ($PM_{2.5}$> 184 µg m^{-3}) during 27% of time spent burning, 7% of time spent dismantling and transporting materials and 6% of time spent eating and drinking (see supplementary Fig S4). Workers performing burning activities also spent close to the longest amount of time in the lowest exposure group ($PM_{2.5}$< 38 µg m^{-3}). The activity-specific distribution of coarse particulate and TSP are similar to findings related to $PM_{2.5}$ (see supplementary Table S6). One notable difference was the increased exposure to coarse PM during the transport of e-waste materials and “other” work activities. Distinctions across activities were less apparent for PM_1.

2.5 Discussion

Wearable camera images can improve time-activity data in an unorganized work environment with substantial occupational exposures. Using images to generate an objective source of high resolution time-activity data greatly reduced participant burden, a strength of this study. The use of image-based TAPs combined with continuous and contemporaneous measures of size-specific PM estimates provided a unique dataset from which high risk job activities and modifiable work behaviors, such as socializing and eating near hazardous work tasks, were identified. Notable findings included high variability in the type and duration of e-waste recovery tasks performed by a worker per shift and over time; poor agreement between self-reported and image-based time-activity data; the highest mean personal $PM_{2.5}$ exposures occurring during burning activities, driven by short-term, peak exposures, followed by sorting and dismantling; $PM_{2.5}$ exposures during long periods of non-work-related activities exceeded the WHO standard in 88% of measured data.

2.5.1 Improved methods for collecting time-activity data

Improved methodologies for collecting accurate time-activity data in challenging informal work settings are needed. In addition to misclassification, social-desirability, and participant fatigue, standard time-activity diaries collected in informal sectors may be limited by language and literacy challenges and the lack of routines and organizational structure in which recall can be grounded [82]. A recent trend to improve personal exposure estimates in large population-based studies with more precise time-activity data has led to the use of location tracking technologies including smart phones and global positioning system (GPS) devices [83–85]. The quality and relevance of such data depend on many factors (e.g. phone technology, wireless provider, network coverage and the amount of time the phone is kept on) that are particularly problematic in Low and Middle Income Countries [83]. GPS data often require extensive cleaning particularly in dense urban areas and indoors [84]. As an alternative, wearable cameras, most commonly the “SenseCam,” have been used to improve memory recall, enhance the assessment of physical activities detected by an accelerometer, and classify environmental characteristics and health behaviors [86–88]. Wearable camera data are also time intensive for the researcher, but can represent an improvement over GPS for the purpose of job identification in informal sectors since the location of a job may change dramatically from day-to-day. Additionally, they eliminate the participant burden and literacy requirements associated with workers keeping active time-activity diaries with 5- or 15-minute resolutions; such high-resolution diaries may be required in job settings with frequent task changes and acute exposures.

Other work has been used to match images and videos with exposure measurements. In a peri-urban Indian environment, Salmon et al. (2018) used wearable cameras combined with personal $PM_{2.5}$ monitoring [89]. Similar to our results, the high time-resolution of the images afforded the ability to detect short-term, peak exposures and revealed activity-exposure relationships not captured in self-reported diaries [89]. In an office building, Luoma and Batterman (2001) used stationary video recordings in combination with area pollutant monitoring to characterize changes in emissions due to recorded work activities [90]. On formal construction sites, video recordings have been used for tracking job progress, personnel and safety monitoring, however development of automated methods for object identification and tracking are still being developed [91,92].

The methodology in this paper to derive image-based TAPs from wearable camera images as a tool to improve occupational exposure assessment proved effective. The TAPs represented the natural flow of activities during a work shift, provided a sufficient level of detail with an interval of only one photo per minute, documented visual details relevant to inhalation exposure and potentially other stressors (e.g. ergonomic), facilitated the estimation of task-specific concentrations, and enabled the transformation of processed image data into a standard time-activity diary of any time resolution that is compatible with standard risk assessment methods. Prior knowledge of e-waste work activities was required to process the images, however previous literature, field visits, and unstructured interviews with workers provided sufficient information.

2.5.2 Self-reported and image-based time activity

Participants reported performing multiple jobs at any given time during their employment at Agbogbloshie. These results are similar to those in previous studies among the same population[20,26,28]. The image-based TAPs agreed with the self-reported data with respect to the types of job tasks most frequently performed on-site with the exception of buying, selling and non-work-related activities as per Tables 1, 2 and S4. The poor observed agreement between self-reported and image-based data from a subset of participant diaries, confirmed that self-reported diaries cannot achieve the degree of task and time precision needed to detect changes in a measured exposure over intervals of five, ten, or even fifteen minutes or distinguish groups of workers on the basis of their exposures and subsequently occupational risks. Diaries may improve survey instrument development by broadly characterizing tasks workers perform (or intend to perform given the availability of materials).

2.5.3 Personal inhalation exposure to PM2.5

Worker tasks associated with peak $PM_{2.5}$ exposures were easily identified using the image-based TAP data. In addition to the specific task itself (e.g. burning), worker movements while transporting e-waste in and out of the fire or periods of variable wind-direction and speed may also contribute to high exposure levels. Lower exposures likely occur while workers are positioned upwind of the fires and other emissions sources and on days with steady winds (supplementary Fig S5 provides images depicting upwind and downwind exposure scenarios).

Personal inhalation exposure during non-work activities are comparable to those during non-burning e-waste recovery tasks. In 43% of the images (n=15) from sitting and eating activities with $PM_{2.5}$ exposures exceeding 448 $\mu g\ m^{-3}$, flames and smoke were identified objects. The location of activities in relation to the source of emissions from burning activities appears to greatly contribute to a worker's $PM_{2.5}$ exposures. The ranking of median exposures by activity further suggest that on days with low-variability in wind-direction, burners may actually be able to control their exposure in contrast to people doing most or all of the other work that are downwind of burning activities. For sites with a prevailing wind direction, such as Agbogbloshie, relocating non-burning jobs to areas typically upwind of burning activities, may markedly decrease mean exposures for those workers. However, this type of site reorganization may increase exposure among residents living in the densely populated communities located on all sides of the site.

2.5.4 Limitations

The use of wearable cameras in research can come with ethical [93] and analytic limitations [87,89]. In occupational settings, camera use is less invasive to an individual's privacy than in home settings. Non-compliance among participants resulted in the exclusion of 9% of the data. The coding process and reviewer training were significant time commitments. Advancements in the use of artificial intelligence and machine learning for image-processing may overcome this burden and introduce new opportunities for exposure science in a world of big data [94]. The test of agreement between self-reported and image-based activities was limited by differences in how a worker and image-reviewer report activities with multiple sub-tasks (e.g. collecting). However, an individual's natural reporting tendencies may actually 'interfere' with achieving exposure and health related objectives. Tasks that are verbal in nature (e.g. buying or selling) may have been misclassified as non-work activities (e.g. sitting), however may also be associated with fewer occupational hazards. Including exemplar images of sitting activities in the worker interviews may have improved classification of these verbal activities. Double-data entry or having a reviewer familiar with the site could reduce activity misclassification. With limited resources for double data entry, we minimized event misclassification with recurrent trainings and worker interviews.

Activity-specific $PM_{2.5}$ estimates are descriptive only and have not been adjusted for ambient $PM_{2.5}$, location, wind, other meteorological factors or the repeated nature of the study design. We did not exclude 0.2% of the data in which $PM_{2.5}$ estimates exceeded the particle counter's upper concentration range (1000 $\mu g\ m^{-3}$). The true concentration was likely higher than the reported measurement, particularly for fine fraction PM (e.g. $PM_{2.5}$). We compared the $PM_{2.5}$ after removing the values >1000 $\mu g\ m^{-3}$ with the full dataset and found no statistically significant difference (Mann-Whitney p-value: 0.7921). "Unusable" images, which were associated with lower $PM_{2.5}$ estimates than in the rest of the data, had to be excluded to avoid misclassification bias. Removed bags were placed by the workers into "safe" or isolated locations, which may be responsible for lowering their associated $PM_{2.5}$ concentrations. Findings from the partial-shift samples are representative of all three seasons in Accra (dry, wet, and windy), but only during the morning and afternoon hours during which participants wore the backpacks. Lastly, a possible “drift” in synchronized device clocks could cause measurement error when examining the association between instantaneous measures [87].

2.5.5 Planned future work

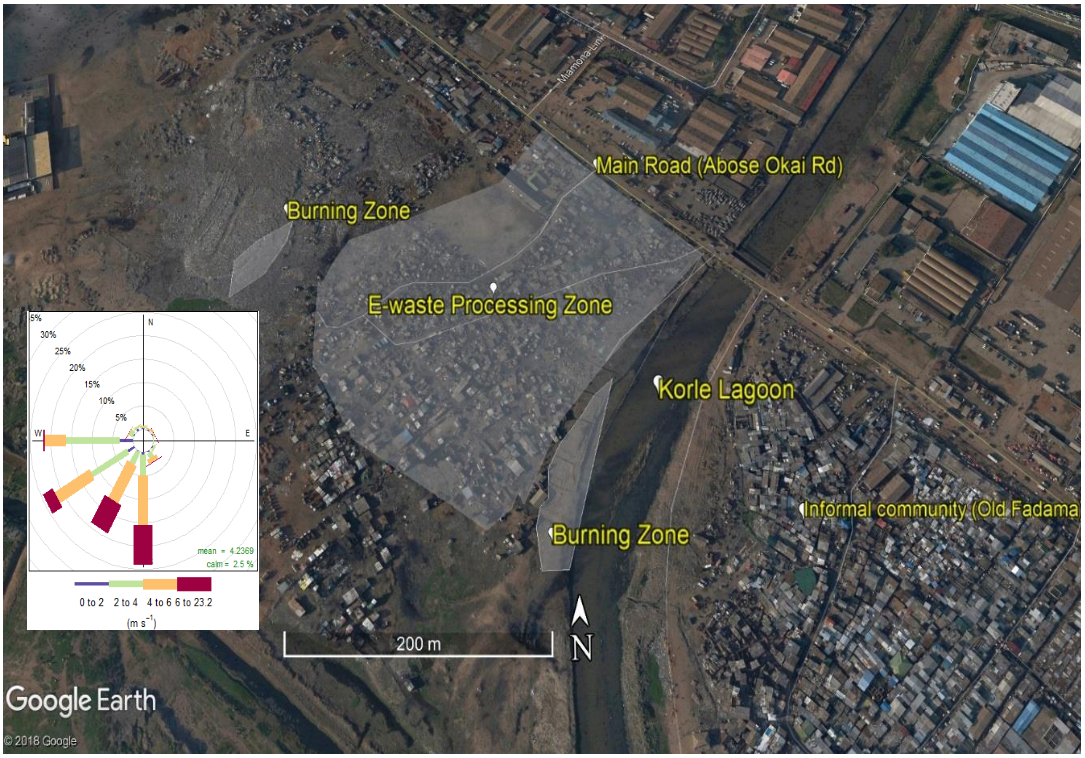
Planned future work will use $PM_{2.5}$ concentrations and paired activities to establish epidemiologic evidence with regard to potentially associated health outcomes, particularly acute responses such as cross-shift changes in pulmonary function. The images highlighted an area of future research, specifically the health effects among women on-site working near burning activities – we observed women selling water to e-waste workers for the purpose of cooling recovered metal after it is removed from the fire. Additionally, studies are needed to address the observed under-employment among other psycho-social job characteristics, such as job stress, limited upward mobility, and effort-reward imbalances experienced by this population [95]. Psycho-social factors are predictive of mental and social functioning disorders, cardiovascular disease risk factors, coronary heart disease and musculoskeletal disorders [96–98] and may independently affect or moderate the health effects caused by the physical exposures. Future proposals to reorganize the worksite and worksite methods should involve an iterative process between workers, local leaders, and multidisciplinary teams including, for example, engineers, exposure experts, epidemiologists, and social scientists and improve conditions for both workers and surrounding communities. The images can subsequently be used in training materials.

2.5.6 Conclusions

The International Labour office (2018) estimates that informal employment accounts for 86% of all employment in sub-Saharan Africa and 62% globally [76]. The undocumented nature of this informal sector, in which men and women face substantial occupational health and safety hazards without physical, social or economic protections, requires innovative and adapted methods for understanding workers’ needs and sources of hazards. Wearable cameras provide a strong alternative to standard recall- and observational- based methods of recording time-activity and reduce participant burden. The use of wearable cameras to improve occupational exposure assessments and provide strong evidence of the risks informal workers experience has broad implications for the improvement of the health and well-being among too many unprotected workers around the globe.

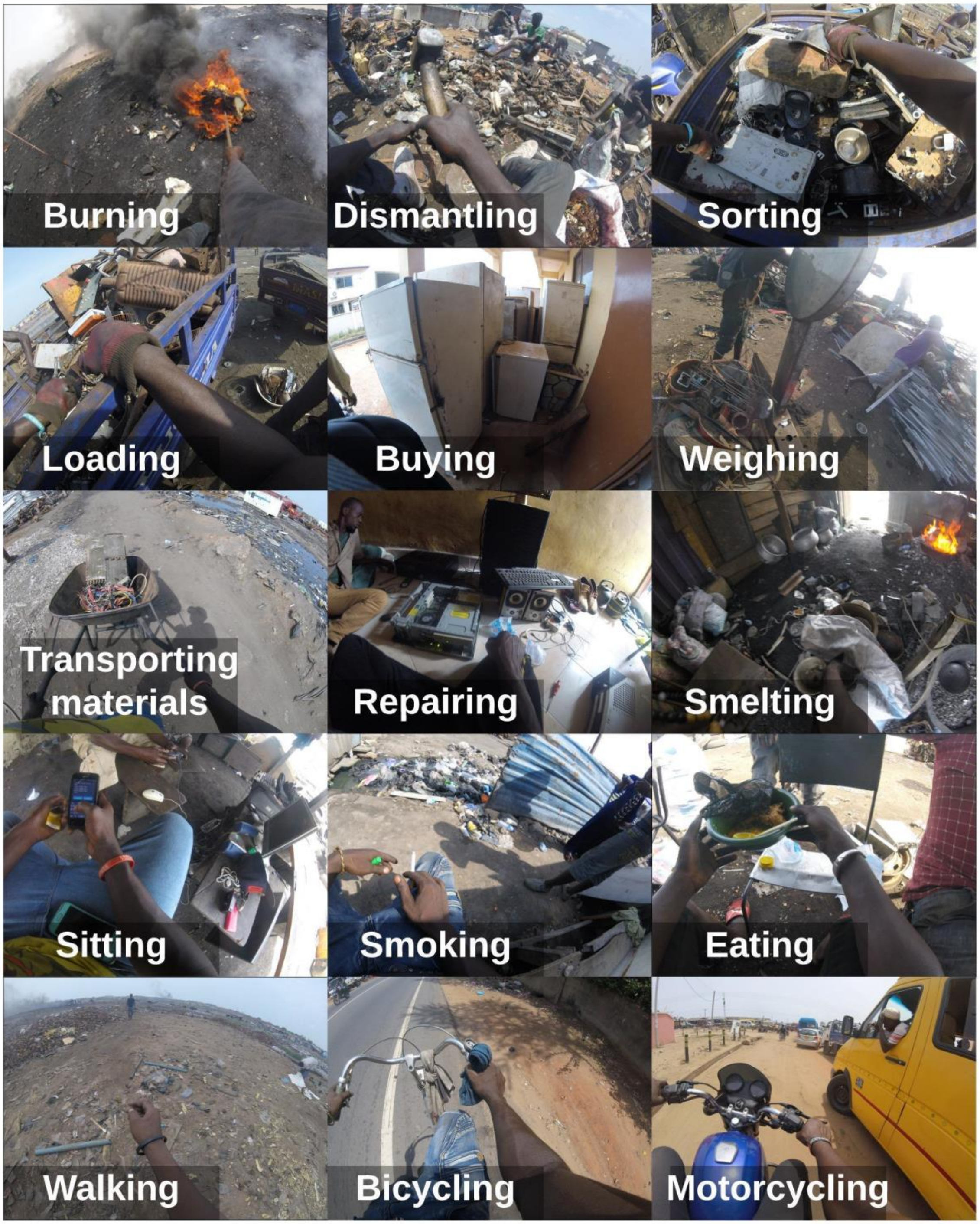
2.6 Figures

Figure 2-1 Site map of the Agbogbloshie e-waste scrap and recovery Site, Accra, Ghana.



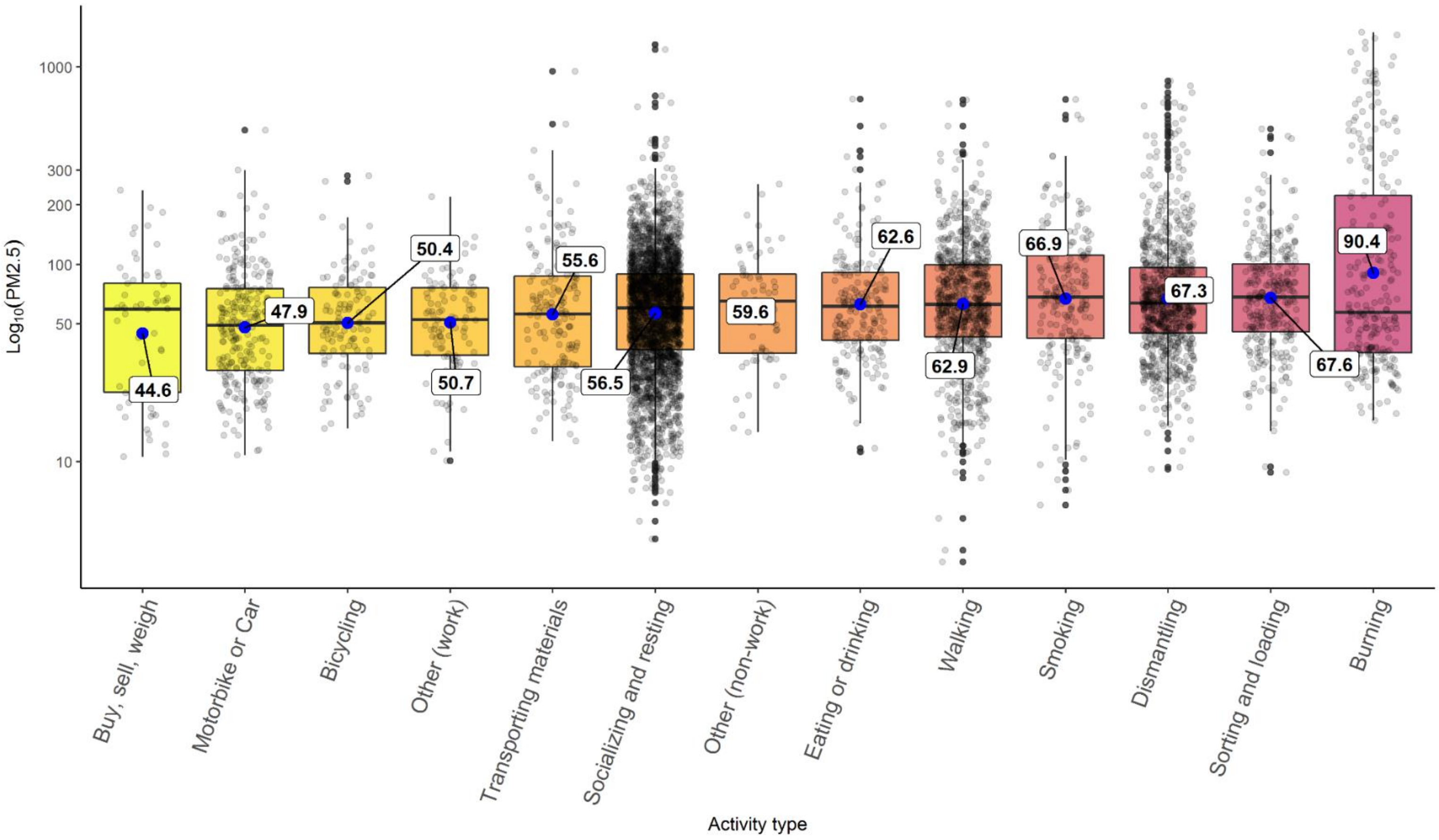
Legend: The Agbogbloshie site is located in Accra, Ghana. The yellow line indicates the main road, Abose Okai Rd, adjacent to the site. The highlighted polygon labelled E-Waste Processing Zone is where dismantling, sorting, weighing, and some trading of e-waste occur. The highlighted polygons labelled Burning Zone indicates where e-waste is burned in open, surface fires. The larger and oldest burning zone is adjacent to the Korle Lagoon. The prevailing winds are south, south-westerlies. Map created using Google Earth Pro V 7.3.2.5776. (10/7/2015). © Google 2018. Wind rose created using Integrated Surface Data collected at the Kotoka International Airport in Accra, Ghana. Data provided by the National Oceanic and Atmospheric Administration's National Centers for Environmental Information (https://www.ncdc.noaa.gov/isd), (accessed on 9/1/2018).

Figure 2-2: Visual activity dictionary



Legend: The images used in this visual task dictionary were taken by wearable cameras worn by study participants during their work day as an e-waste recovery worker. The exemplar images demonstrate how time-activity data can be derived using time-lapse images.

Figure 2-3: Personal inhalation exposure to $PM_{2.5}$ by activity type (image-based) and sorted by ascending geometric mean.



Legend: For each boxplot, the midline represents the median value and the labelled blue point describes the geometric mean. The upper and lower limits of the box represent the 75th and 25th percentiles respectively. The "whiskers" extend to 1.5 times the interquartile range from the top and the bottom of the box. The points beyond that distance are represented by individual points. The jittered black points show the density of data by activity; each point represents a 5-minute $PM_{2.5}$ average value

2.7 Tables

Table 2-1: Activities performed by e-waste worker participants during 170 partial shift samples and derived using wearable camera time lapse images (N=31,837).

	No. of Events[a]	Duration (minutes)	Total (minutes)
Task Category	**N**	**Mean (SD)**	**N (%)**
Work-related events	**212**	**41.5 (48)**	**8,806 (27.7)**
Burning	26	47.7 (42)	1,240 (3.9)
Dismantling	75	58.2 (63)	4,362 (13.7)
Sorting and loading	43	34.5 (43)	1,483 (4.7)
Buy, sell, weigh	16	18.6 (12)	297 (0.9)
Transporting materials	40	21.3 (21)	851 (2.7)
Repair	1	16.0 (NA)	16 (0.1)
Other	11	50.6 (30)	557 (1.7)
Non-Work related events	**344**	**49.6 (52)**	**17,072 (53.6)**
Sitting	260	56.4 (55)	14,670 (46.1)
Smoking while sitting	24	43.4 (47)	1,041 (3.3)
Eating or drinking while sitting	44	23.5 (26)	1,033 (3.2)
Other	16	20.5 (18)	328 (1.0)
Transportation related events	**354**	**16.8 (16)**	**5,959 (18.7)**
Walking	256	16.1 (11)	4,126 (13.0)
Bicycling	28	20.5 (15)	575 (1.8)
Motorbike or Car	70	18.0 (27)	1,258 (4.0)
Total[b]	**910**	**35.0 (43)**	**31,837 (100.0)**

[a] An event" is defined as a consecutive series of images of variable length depicting one sustained activity; event duration can range from 1 to n minutes. [b] Out of a grand total of 35,588 images, 31,837 images were used after excluding n=3,149 unusable images (321, 789 and 2039 images from waves I, II and III respectively) during which the sampling backpack was removed by the participant; and n= 602 images taken in the staging area where devices were turned on and off and participants completed registration.

Table 2-2: Activity breakdown from self-reported diaries (30-min resolution) and matched image-based time-activity patterns (30-min resolution) collected during wave II from a subset of e-waste worker participants (N=51).

		Self-Reported[a]			Image-Based[b]		
		No. of 30-min periods	Time (30-min periods)		No. of 30-min periods	Time (30-min periods)	
		N	Mean (SD)	Total (%)	N	Mean (SD)	Total (%)
Activities							
Burning		7	4.6 (2)	32 (9.2)	2	4. (3)	8 (2.3)
Dismantling		21	6.9 (4)	145 (41.5)	11	4.3 (3)	47 (13.5)
Sorting and loading[c]		5	8.0 (5)	40 (11.5)	10	2.8 (2)	28 (8.0)
Buy, sell, weigh		8	5.1 (3)	41 (11.7)	3	2.3 (1)	7 (2.0)
Repair		NA	NA	NA	1	2. (NA)	2 (0.6)
Transporting materials[c]		1	9.0 (NA)	9 (2.6)	7	1.3 (0)	9 (2.6)
Other (Work)		2	1.5 (1)	3 (0.9)	3	2.7 (2)	8 (2.3)
Non-Work or transport		22	3.6 (3)	79 (22.6)	25	9.6 (8)	240 (68.8)
Total		66	5.3 (4)	349 (100)	62	5.6 (6)	349 (100)

[a] Self-reported time-activity diaries (N=51) from Wave 2 matched with image-based time-activity data by subject-ID and date-time .[b] Image-based time-activity patterns (N=51) from Wave 2 matched with self-reported time-activity data by subject-ID and date-time. [c] Sorting, loading and transporting materials were combined into "Material movement and transport" prior to testing agreement between the two sources of data with a kappa statistic.

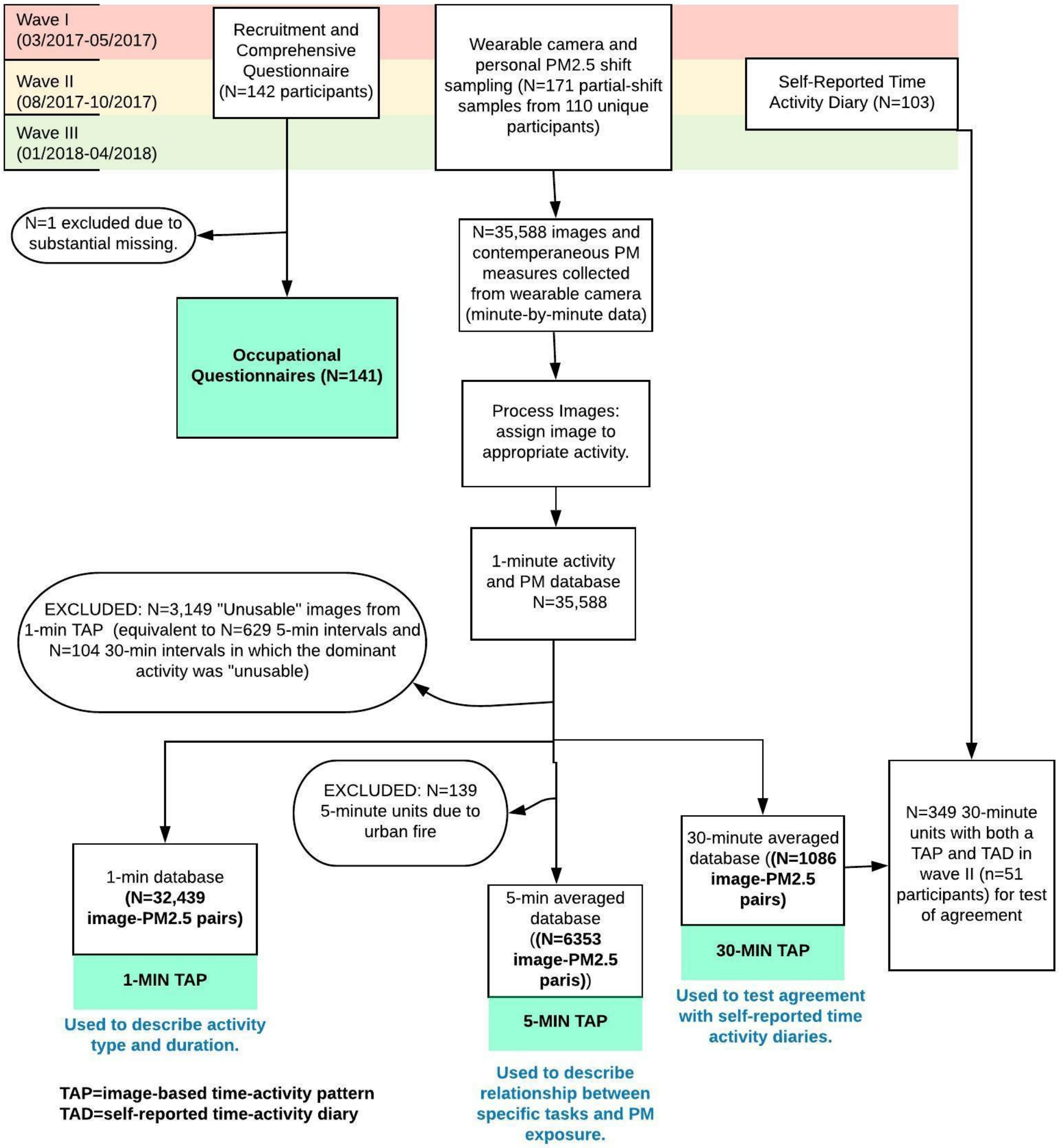
Table 2-3: Distribution of size-specific $PM_{2.5}$ (µg m^{-3}) by activity type (image-based).

Activities[a]		No. of 5-min periods	$PM_{2.5}$ (µg m^{-3})								
		N	Geometric mean (SD)	Arithmetic mean (SD)	Minimum	P5	P25	P50	P75	P95	Maximum
Work-related events		**1755**	**66.7 (2.2)**	**100.2 (144.2)**	**8.8**	**22.7**	**39.9**	**62.1**	**96.7**	**325.9**	**1,501.4**
	Burning	249	90.4 (3.3)	202.8 (300.9)	16.1	24.5	35.6	57.0	223.0	912.4	1,501.4
	Sorting and loading	301	67.6 (1.9)	82.8 (62.5)	8.8	24.4	45.4	68.2	100.2	183.0	485.6
	Dismantling	864	67.3 (2.0)	89.2 (95.6)	9.1	25.9	44.8	63.5	95.9	221.5	850.5
	Transporting materials	169	55.6 (2.2)	78.3 (95.3)	12.7	18.6	30.2	55.8	87.1	214.7	950.6
	Other	110	50.7 (1.8)	58.7 (32.5)	10.1	19.4	34.6	52.4	76.1	114.8	220.1
	Buy, sell, weigh	61	44.6 (2.3)	61.0 (49.5)	10.6	12.8	22.4	59.1	80.0	156.4	237.1
	Repair	3	41.1 (1.1)	41.1 (2.8)	38.6	38.8	39.6	40.7	42.4	43.8	44.1
Non-Work related events		**3311**	**57.5 (2.0)**	**72.7 (62.8)**	**4.0**	**16.4**	**37.4**	**61.0**	**90.5**	**161.7**	**1,296.9**
	Smoking while sitting	210	66.9 (2.2)	90.8 (85.7)	6.0	13.5	42.1	68.3	111.2	219.8	685.3
	Eating or drinking while sitting	201	62.6 (1.9)	80.1 (77.1)	11.2	25.6	41.1	61.0	90.7	195.0	687.7
	Other	64	59.6 (1.9)	72.7 (48.0)	14.1	20.8	35.4	65.0	89.2	153.4	254.2
	Sitting	2836	56.5 (2.0)	70.9 (59.7)	4.0	16.2	36.9	60.1	88.9	156.1	1,296.9
Transportation related events		**1171**	**58.1 (2.0)**	**73.7 (59.7)**	**3.1**	**18.3**	**37.7**	**59.2**	**92.1**	**174.5**	**679.5**
	Walking	807	62.9 (2.0)	79.8 (63.8)	3.1	18.2	42.7	62.6	99.3	188.1	679.5
	Bicycling	115	50.4 (1.8)	60.4 (42.0)	14.7	19.4	35.3	50.4	76.4	123.3	281.4
	Motorbike or Car	249	47.9 (1.9)	60.0 (49.2)	10.8	18.2	29.0	49.0	75.2	135.3	479.0
Total[b]		**6239**	**60.2 (2.1)**	**80.6 (92.9)**	**3.1**	**18.6**	**38.2**	**61.0**	**92.5**	**186.2**	**1,501.4**

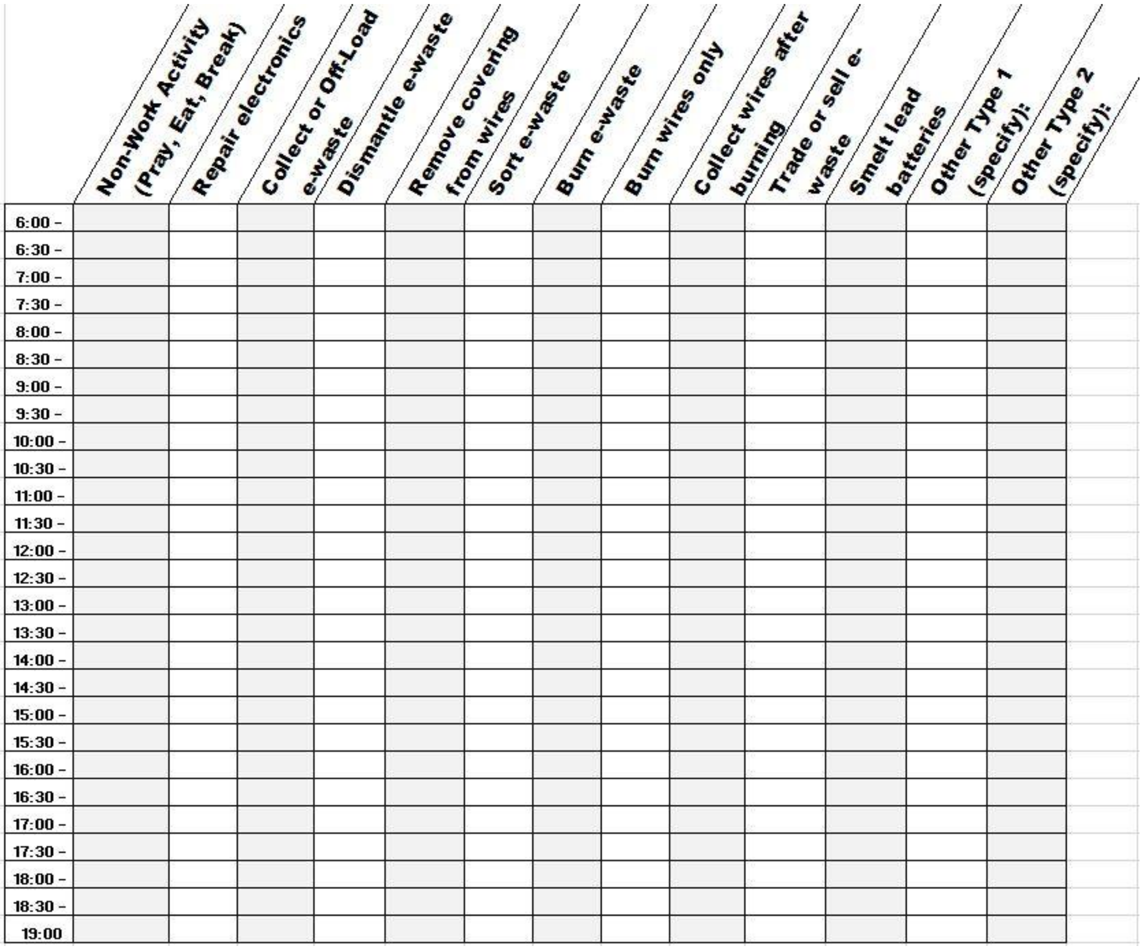
[a] Activities used in this table were derived from image-based time-activity patterns. [b] Out of a grand total of 7,121 5-min averaged intervals, 6,239 were used after excluding n=629 5-min intervals that were unusable due to removal of the sampling backpack by the participant; n= 114 5-min intervals taken in the staging area where devices were turned on and off and participants completed registration; and n=139 5-min intervals recording PM levels on a day with an adjacent urban fire.

2.8 Supplementary Tables and Figures

Supplemental Figure 2-1 Data collection and sampling framework



Supplemental Figure 2-2: Self-reported time-activity diary



	Non-Work Activity (Pray, Eat, Break)	Repair electronics	Collect or Off-Load e-waste	Dismantle e-waste	Remove covering from wires	Sort e-waste	Burn e-waste	Burn wires only	Collect wires after burning	Trade or sell e-waste	Smelt lead batteries	Other Type 1 (specify):	Other Type 2 (specify):
6:00 –													
6:30 –													
7:00 –													
7:30 –													
8:00 –													
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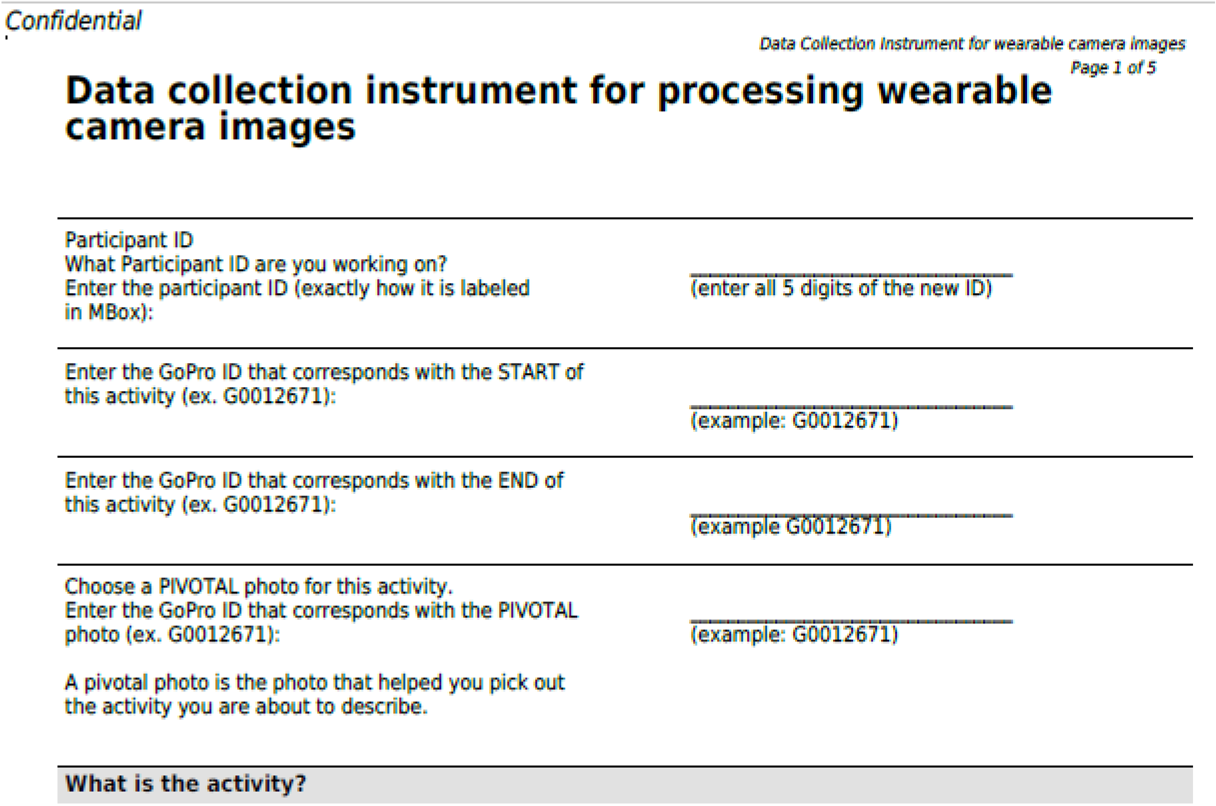
Details on task categories used to test agreement with image-based time-activity data: Prior to testing the agreement between self-reported and image-based time-activity data, specific job categories were combined. These categories were created by combining activities that shared certain identifiable visual cues (e.g. visible open flames), physical effort, and materials. Agreement was tested for the following categories: burning, dismantling, material movement and organization, buy-sell-weigh, repairing, smelting, other (work-related), and non-work-related.

From the self-reported diaries *Burning* is comprised of “burn e-waste”, “burn wires only” and “collect wires after burning”; *Material movement and transport* is comprised of “collect or off-load e-waste” and “sort e-waste”; *Dismantling* is comprised of “dismantle e-waste” and “remove covering from wires”; *Buy-sell-weigh* is comprised of “trade of sell e-waste” and “weighing e-waste” which was written into the “other (work)” category. All other categorizes remained unchanged.

From the image-based data collection tool: *Burning* is comprised of “burning wires”, “burning material other than wires”, and “starting or igniting a fire”; *Dismantling* is comprised of “dismantling, pounding or breaking”, and “stripping casings off of wires”; *Material movement and organization* is comprised of “on-/off-loading”, “sorting, gathering”, and “transporting materials”; *Buy-sell-weigh* is comprised of “trading or selling e-waste” and “weighing”. All other categorizes remained unchanged.

Supplemental Figure 2-3: Instrument for collecting data from time-lapse images.



Confidential

Data Collection Instrument for wearable camera images
Page 1 of 5

Data collection instrument for processing wearable camera images

Participant ID What Participant ID are you working on? Enter the participant ID (exactly how it is labeled in MBox):	__________________________________ (enter all 5 digits of the new ID)
Enter the GoPro ID that corresponds with the START of this activity (ex. G0012671):	__________________________________ (example: G0012671)
Enter the GoPro ID that corresponds with the END of this activity (ex. G0012671):	__________________________________ (example G0012671)
Choose a PIVOTAL photo for this activity. Enter the GoPro ID that corresponds with the PIVOTAL photo (ex. G0012671): A pivotal photo is the photo that helped you pick out the activity you are about to describe.	__________________________________ (example: G0012671)

What is the activity?

Scan the list of activities below and think about whether the subject wearing the camera is engaged in a task related to their work (WORK TASK) , is doing something else (OTHER tasks) or is in-between tasks (TRANSPORT).

○ Work task
○ Other task
○ Transport or In-Between tasks
○ Backpack with camera removed
○ Staging area

Work Tasks:
Burning (any kind)
Wire Stripping
Dismantling, pounding, breaking
Repairing
On- or Off-Loading,
Gathering, sorting
Trading, selling, weighing
Smelting (any material)

Other Tasks:
On a break
Praying
Eating or drinking
Taking a nap
Communicating with others/ on the Cell Phone
In the washroom
Other

Transport or In-Between tasks:
Subject is on the move

Staging Area:
Getting the backpack on, off or adjusted

WORK RELATED ACTIVITY

Which task best describes what they are doing?

☐ Burning wires
☐ Burning material other than wires
☐ Starting or igniting a fire
☐ Stripping casings off of wires
☐ Dismantling, pounding, breaking
☐ Repairing an electronic (may be hard to tell, but ultimate goal is not to break it apart)
☐ On- or Off-Loading
☐ Sorting, gathering
☐ Weighing
☐ Trading or Selling
☐ Smelting (melting something in a pot over flames)
☐ Other
(Check ALL that apply)

Since you indicated "other", please describe:

____

What fuel source is being used to get the fire going?	☐ Styrofoam ☐ Petrol/kerosene ☐ Tires ☐ Only lighters and matches ☐ Saw dust ☐ Coconut Shells ☐ Other ☐ I can't tell (Check ALL that apply)
Since you indicated "other", please describe:	________________________
How confident are you that the subject is doing the task you described: "[task_1]"?	Low confidence Medium confidence High confidence (Place a mark on the scale above)

NON-WORK RELATED ACTIVITY

Which of these activities best describe the "[task]" that the subject is engaged in?	☐ Smoking ☐ Eating, drinking ☐ Praying ☐ Rest, Cell Phone, communicating ☐ In the washroom ☐ Cooking ☐ Shopping or at the market ☐ Other (Check ALL that apply)
Since you indicated "other", please describe:	________________________
Are people performing any type of e-waste recycling nearby?	○ Yes ○ No

TRANSPORTATION RELATED

What type of transportation method is the participant engaged in?	○ Walking ○ Riding a bicycle ○ Riding a motorbike ○ Sitting or driving in an automobile (car, bus, truck) ○ I am not sure
Is the subject moving work materials by carrying them or pushing/pulling a cart?	○ Yes ○ No ○ I'm not sure

OBJECT SEARCH

Do you see any of these objects throughout this activity?
If you like, you can list objects found in other photos related to this task.

☐ Fire
☐ Smoke
☐ Ash
☐ Pot over flames
☐ Indoor Cook Stove that is being used
☐ Cigarette or someone smoking
☐ Tools (hammer, chisel, fire poker)
☐ Wires, copper wires, wire casings
☐ Electronic or car parts (can be broken)
☐ Metal shavings, chunks or pieces
☐ Sack with metal or parts
☐ Scale or weigh station
☐ Wheelbarrow or cart
☐ Moving motorbike or automobiles
☐ Food or drink
☐ Market, shop or food vendor
☐ NONE OF THE ABOVE
(Check ALL that apply)

How close is the participant to the FIRE or SMOKE?
(Choose the BEST match)

○ Very close/ In the smoke
○ A few body lengths away
○ 10 meters or farther
○ I can't tell

NEW SECTION: IMMEDIATE SURROUNDINGS OR "MICRO-ENVIRONMENT"

For this activity (even if you are not completely sure what it is), which category best describes the immediate surroundings of the participant during this task?

○ Completely outdoors (no roof or any walls)
○ Completely Indoors (all windows and doors are closed)
○ Partially indoors (could include just a roof, some walls or open windows and doors)
○ the participant went to multiple locations

Which location did the participant spend the most time in during this activity?

○ Completely outdoors (no roof or any walls)
○ Completely Indoors (all windows and doors are closed)
○ Partially indoors (could include just a roof, some walls or open windows and doors)

Please check off any of the following features that match the enclosure that the subject is in:

☐ One or more walls
☐ Open window or door
☐ Finished floor, carpet or rug
☐ Roof (indicators may be shade or a shadow)
(Check ALL that apply)

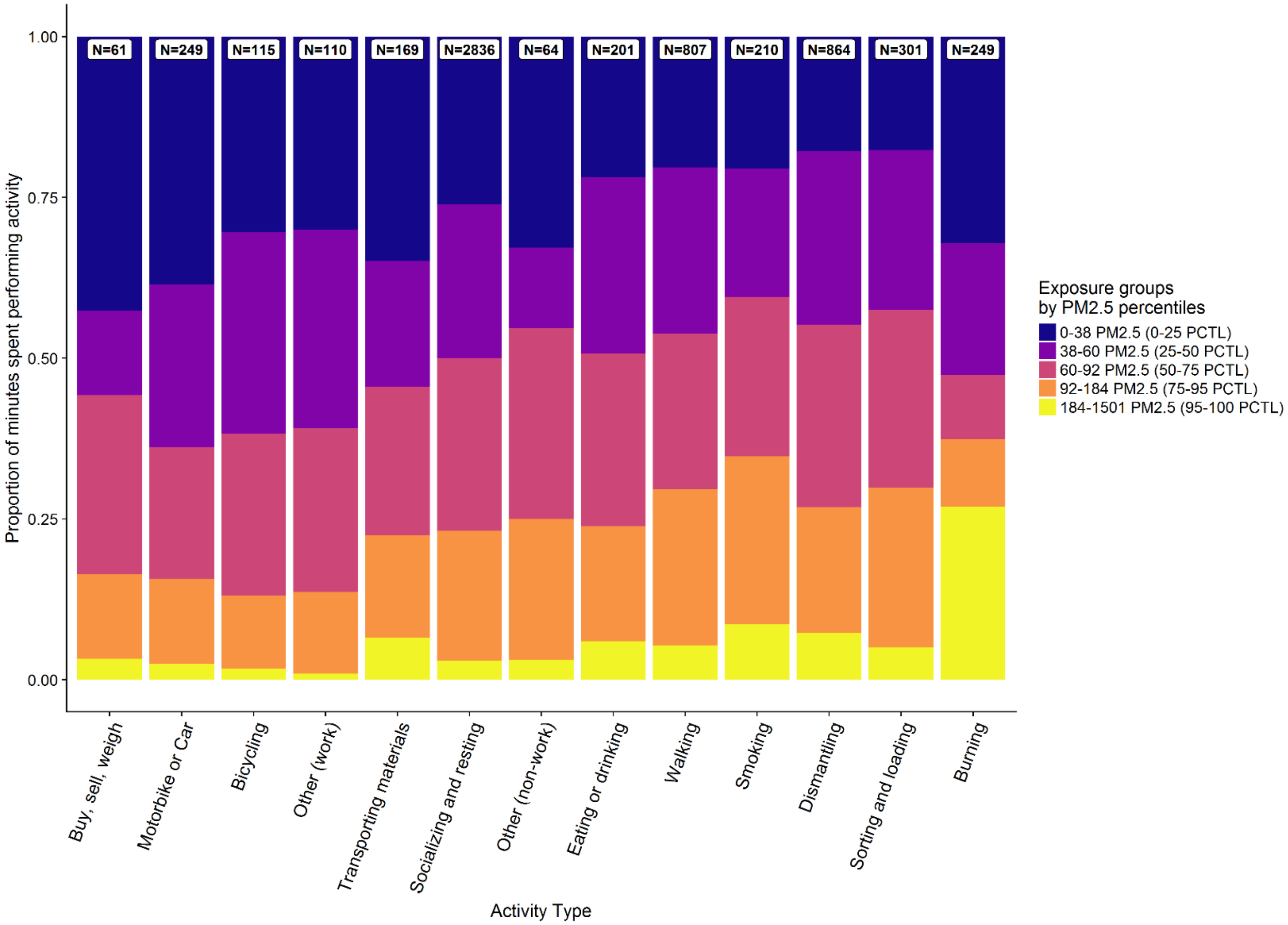
All Done!

You have finished all questions for this activity
Nice Job
Use the notes box to tell us anything else you think we might want to know.

____

When you are done, please SAVE the file, enter a new activity for this participant or go on to the next.

Supplemental Figure 2-4: Proportion of time spent performing specific activities by $PM_{2.5}$ exposure group.



Supplemental Figure 2-5: Images depicting burning activities characterized by high and low exposures to $PM_{2.5}$

Legend: Images taken using a wide-angle GoPro Hero 4 © camera strapped to the forward facing shoulder strap of a personal sampling backpack worn by a participant in the GeoHealth study.

Supplemental Table 2-1 Dictionary of e-waste related activities

1) *Burning*: *v*aluable e-waste components covered in plastics are placed into open, surface fires to melt away the unwanted plastics. Metal rods are a tool used during burning to turn and move metal in and out of the fire.
2) *Dismantling*: e-waste is manually dismantled using physical force and tools including hammer, chisel, screwdriver, pliers and cutters. We included wire stripping in the dismantling category as it is typically performed in the same setting or adjacent to dismantling tasks.
3) *Sorting:* like e-waste parts and components are sorted into piles and put into sacks either for further processing, burning or selling.
4) *On-Off loading*: e-waste and scraps are loaded on and off-carts and wheel barrows following collection or processing to be moved from one location to another.
5) *Buying/trading*: collected (unprocessed) e-waste or recovered metals (predominantly copper, aluminum and steel) and valuable parts are purchased for e-waste processing or selling at a market. Exchange of money and goods were used to identify buying and trading.
6) *Weighing*: weighing or “scaling” is performed on site to determine the weight of the final product to be sold (typically copper, steel or aluminum). Weigh stations (large scales) are identifiable in the images.
7) *Transporting materials* can be done on or off-site. When performed off-site, materials are collected or “scavenged” from neighborhoods in Accra for free or a nominal fee. This work is typically performed using a cart, however items are also picked up by bicycle/tricycle or automated vehicles. We indicated if a worker was “transporting materials” if he was either walking, bicycling, or on a motorbike and visibly carrying or pushing e-waste materials. Location can’t be determined.
8) *Repairing* electronic or electrical devices for resale or personal use.
9) *Smelting* metals including aluminum or lead are performed on-site. Workers reported that smelting lead used to occur more frequently at Agbogbloshie, but is now rare.

Supplemental Table 2-2 Chronology of activities and output for processing wearable camera images

Step	Activity	Output	Location
1	Visit and observe physical worksite	List of specific tasks and their associated visual cues; If possible, a map of the primary work space's general layout and major landmarks.	Field
2	Deploy wearable cameras to capture images	Participant specific folders with time-stamped images.	Field
3	Use output from step 1 and descriptions of the work processes from previous literature to inform a preliminary screening of a subset of digital images.	Lists of identifiable tasks (i.e. work, non-work and transportation related), common behaviors and themes; List of objects and landmarks predictive of task and exposure; Method for the use of objects and landmarks to validate assignment and predict exposure; And list of image quality issues. Process complete when no new visual themes are identified by reviewing additional images (saturation).	Office
4	Design a data collection instrument using output from steps 1 and 3.	Data collection instrument with each entry representing one event-unit. Skip logic and quality controls are recommended to streamline the process and improve data entry results.	Office
5	Design training materials	Training materials with exemplar images for each specific task assignment and data entry protocol.	Office
6	Train reviewers and perform pilot data entry	Database of task sequence and task-specific details for a subset of participants.	Office
7	Return to physical worksite and meet with workers to review accuracy of task assignment using exemplar images.	Agreement between worker and reviewer assigned tasks.	Field
8	Use results from step 7 to revise data collection instrument and update training.	Modified training protocol and data collection instrument.	Office
9	Perform single or double data entry.	Database of task sequence and task-specific details for all study participants.	Office
10	Export final database to render TAPS and merge	Minute-by-minute database of event sequence, a time-activity pattern (TAP) and contemporaneous $PM_{2.5}$ concentration.	Office

	with contemporaneous exposure estimates.		
11	Program a method for averaging the database to render TAPs with desired time-resolution.	Averaged database of time-resolved TAPs. For the averaged 5-min database a minimum of three minutes/images were required. The event chosen to represent the averaged unit was performed most in the interval. Equally split intervals choose the first of the two activities. A similar protocol was followed to create an averaged database with a 30-min resolution, however the selection criteria prioritized work-related activities even if other non-work related events had a longer duration in the same time interval.	Office

Supplemental Table 2-3 Socio-demographic and job characteristics of e-waste worker participants (n=141).

Characteristic		
Sex (%)	Male	**Overall**
Age (mean (range))		141 (100.0)
Country (%)	Ghana	26.9 (16-50)
	Other	138 (97.9)
Region (%)	Northern	3 (2.1)
	Other	136 (96.5)
Language (%)	Dagbani	5 (3.5)
	Other	130 (92.2)
	Missing	6 (4.3)
Religion (%)	Muslim	5 (3.5)
	Other	132 (93.6)
	No religion	6 (4.3)
Marital status (%)	Married	3 (2.1)
	Single	80 (56.7)
	Other	56 (39.7)
	Missing	2 (1.4)
Education (%)	No education	3 (2.1)
	Primary education	45 (31.9)
	Junior secondary school	37 (26.2)
	Secondary school	41 (29.1)
	Higher	16 (11.3)
	Missing	1 (0.7)
Daily Income (%) 4GHS= 1USD	<= GHS 20	1 (0.7)
	GHS 21-40	26 (18.4)
	GHS 41-60	46 (32.6)
	GHS 61-100	38 (27.0)
	>100 GHS	14 (9.9)
Home location (%)	On or within 1km of e-waste site	17 (12.1)
	Off e-waste site(> 1km)	124 (87.9)
	Missing	15 (10.6)
Years at Agbogbloshie (mean (range))	8.62 (.08-25)	2 (1.4)
Hours worked/ day (mean (range))		
Work on Saturday or Sunday (%)	Rarely	9.58 (4-15)
	Frequently	12 (8.5)
	Always	21 (14.9)
	Missing	102 (72.3)

Supplemental Table 2-4 Worker self-reported job task history since arriving to the Agbogbloshie e-waste recovery site (n=141)

Tasks	"Ever" performed job	"Currently" perform job	Primary job in the past 3 months[a]	Primary job in the past 1 month[a]	Months ever performing job	No of days in past week performing job	No of hr during last work day performing job
	N (%)	N (%)	N (%)	N (%)	Mean (range)	Mean (range)	Mean (range)
Burning e-waste	84 (59.6)	82 (58.2)	26 (18.4)	23 (16.3)	67.9 (1-216)	4.0 (1-7)	3.5 (1-13)
Dismantling	111 (78.7)	104 (73.8)	52 (36.9)	60 (42.6)	83.9 (1-253)	4.1 (1-7)	4.8 (1-13)
Collecting e-waste	65 (46.1)	53 (37.6)	19 (13.5)	17 (12.1)	71.9 (1-253)	3.7 (1-7)	4.4 (1-13)
Sorting	54 (38.3)	48 (34.0)	1 (0.7)	1 (0.7)	73.2 (1-253)	2.8 (1-7)	1.8 (1-5)
Trading, selling	89 (63.1)	85 (60.3)	24 (17.0)	21 (14.9)	107.8 (1-265)	3.8 (1-7)	3.6 (1-13)
Weighing	6 (4.3)	6 (4.3)	2 (1.4)	4 (2.8)	71.6 (8-149)	6.3 (6-7)	7. (2-12)
Repairing electronics	14 (9.9)	13 (9.2)	2 (1.4)	3 (2.1)	79.8 (9-228)	3.5 (1-7)	3.7 (1-10)
Smelting	12 (8.5)	12 (8.5)	0 (0.0)	0 (0.0)	75.9 (2-216)	1.6 (1-3)	2.3 (1-4)
Other	9 (6.4)	7 (5.0)	10 (7.1)	7 (5.)	32.6 (2-100)	1.3 (1-21)	8.9 (3-13)

[a] Column does not add to total due to missing (n=5).

Supplemental Table 2-5 Distribution of event duration by activity type (image-based).

	Events[a]	Duration in minutes			
	N	min	med	mean	max
Work-related events					
Burning	26	7	33.5	47.7	147
Dismantling	75	2	33.0	58.2	275
Sorting and loading	43	1	17.0	34.5	170
Buy, sell, weigh	16	3	17.0	18.6	49
transporting materials	40	1	13.5	21.3	90
Repair	1	16	16.0	16.0	16
Other	11	13	48.0	50.6	94
Non-Work related events					
Sitting	260	1	35.5	56.4	282
Smoking while sitting	24	8	33.5	43.4	228
Eating or drinking while sitting	44	7	15.5	23.5	155
Other	16	1	17.5	20.5	71
Transportation related events					
Walking	256	1	14.0	16.1	63
Bicycling	28	6	18.5	20.5	51
Motorbike or Car	70	1	8.5	18.0	164

[a] An event” is defined as a consecutive series of images of variable length depicting one sustained activity; event duration can range from 1 to *n* minutes in length.

Supplemental Table 2-6 Summary of size-specific particulate matter by activity type (image-based).

		No. of 5-min periods	PM 1 (µg/m3)			COARSE PM (µg/m3)			Total Suspended Particulate		
Category		N (%)	GM (SD)	Mean	Median	GM (SD)	Mean	Median	GM (SD)	Mean	Median
Work related events		**1757 (28.2)**	**47. (2.)**	**59.2**	**48.4**	**105.8 (2.5)**	**167.3**	**97.1**	**214.6 (2.2)**	**312.5**	**196.4**
	Burning	249 (4.0)	47.5 (2.2)	63.0	48.0	111.9 (3.1)	235.3	90.3	238.7 (2.9)	462.2	189.4
	Dismantling	864 (13.8)	48.3 (1.9)	59.0	50.2	104.3 (2.1)	144.6	97.9	208.7 (2.)	269.9	196.4
	Collect, sort, load	301 (4.8)	53.8 (1.9)	67.4	55.2	108.7 (2.5)	170.5	95.3	228.6 (2.2)	324.1	199.6
	Buy, sell, weigh	61 (1.0)	39. (2.2)	51.2	51.6	77.2 (3.7)	155.7	106.1	156.6 (2.9)	253.8	175.0
	transporting materials	169 (2.7)	37.8 (2.1)	50.7	34.8	112.6 (2.6)	180.1	108.9	216.5 (2.4)	321.2	197.6
	Repair	3 (0.0)	41.1 (1.1)	41.1	40.7	86.5 (2.)	102.9	62.0	152.7 (1.9)	176.3	111.4
	Other (work)	110 (1.8)	39.8 (1.9)	47.8	39.4	105.1 (2.9)	171.6	98.1	209.7 (2.4)	299.5	193.7
Non-Work related events		**3311 (53.1)**	**47.3 (2.1)**	**61.6**	**49.6**	**66.6 (2.3)**	**99.0**	**67.5**	**149.3 (2.)**	**196.2**	**152.8**
	Sitting	2836 (45.5)	47.2 (2.1)	60.9	49.9	66.1 (2.3)	97.8	66.8	147.2 (2.)	193.4	150.8
	Smoking while sitting	210 (3.4)	57.1 (2.3)	80.0	60.2	55.8 (2.1)	72.0	62.8	148.4 (1.9)	179.7	163.3

	Eating or drinking while sitting	201 (3.2)	41.6 (2.1)	55.3	39.5	78.8 (2.4)	117.2	73.5	170.4 (2.1)	223.7	164.5
	Other (non-work)	64 (1.0)	38.9 (2.2)	52.6	36.3	101.5 (2.6)	183.0	93.0	189.5 (2.3)	287.5	182.8
Transportation related events		**1171 (18.8)**	**47.4 (2.1)**	**62.8**	**48.2**	**89.2 (2.4)**	**134.2**	**92.7**	**187.9 (2.1)**	**251.6**	**191.7**
	Walking	807 (12.9)	52.3 (2.1)	69.0	53.2	90.7 (2.3)	129.6	93.7	193.6 (2.)	250.1	196.0
	Bicycling	115 (1.8)	43.2 (2.)	54.6	43.6	93.6 (2.3)	128.2	100.7	177.7 (2.)	224.6	172.9
	Motorbike or Car	249 (4.0)	36.1 (2.)	46.5	33.9	82.6 (3.)	151.8	80.6	175.2 (2.5)	269.0	172.1
Total		**6239 (100)**	**47.2 (2.1)**	**61.1**	**48.8**	**80.2 (2.4)**	**124.9**	**78.7**	**172.7 (2.1)**	**239.3**	**171.1**

3 Chapter 3: Opportunities and Challenges in Reducing Personal Inhalation Exposure to Air Pollution among Electronic-Waste Recovery Workers in Ghana

3.1 Abstract

Background: Informal sector electronic-waste (e-waste) recovery produces toxic emissions resulting from burning e-waste to recover valuable metals.

Objectives: To identify high-risk worker groups by measuring relative levels of personal inhalation exposure to particulate matter (PM) of fine ($\leq$2.5 µm) and coarse (2.5-10 µm) fractions ($PM_{2.5}$ and $PM_{2.5-10}$, respectively) across work activities among e-waste workers, and to assess how wind conditions modify levels of PM by activity and site location.

Methods: At the Agbogbloshie e-waste site in Accra, Ghana, 170 partial-shift PM samples and time-activity data were collected from participants (N=105) enrolled in the GeoHealth cohort study. Personal sampling included continuous measures of size-specific PM from the worker's breathing zone and time-activity derived from wearable cameras. Linear mixed models, adjusted for background $PM_{2.5}$, study wave, day-of-week, temperature and relative humidity, were used to estimate changes in personal $PM_{2.5}$ and $PM_{2.5-10}$ associated with e-waste activities and evaluate effect modification by wind speed and direction.

Results: Mean ($\pm$ standard deviation) personal $PM_{2.5}$ and $PM_{2.5-10}$ concentrations were 80 µg m^{-3} ($\pm$81) and 123 µg m^{-3} ($\pm$139), respectively. The adjusted mean $PM_{2.5}$ concentration for burning e-waste was 88 (µg m^{-3}), a 28% increase (95% confidence interval: 10.7%, 48.2%) above the adjusted mean concentration during non-recovery activities (e.g., eating or drinking). Transportation-related and burning activities were associated with the highest $PM_{2.5-10}$ concentrations. Periods of frequent changes in wind direction were associated with higher $PM_{2.5}$ concentrations when burning. Periods of higher wind speeds were associated with higher $PM_{2.5-10}$ concentrations when dismantling e-waste downwind of the burning-zone.

Discussion: Breathing zone concentrations of $PM_{2.5}$ and $PM_{2.5\text{-}10}$ considerably exceeded health-based air-quality guidelines for all workers regardless of activity. The greatest reductions in personal exposure for all workers will come from the replacement of burning practices with safer and more efficient methods of metal extraction viable in low and middle-income countries.

3.2 Introduction

The disease burden from ambient particulate matter (PM) pollution exposure disproportionately falls on individuals in low- and middle-income countries (LMICs)[57]. Workers, especially those in LMICs where enforcement of any existent occupational safety regulations often is minimal, are exposed to both environmental and occupational sources of PM. The Global Burden of Disease study estimates that 488,000 deaths were attributable to occupational exposure to “particulate matter, gases and fumes” in 2017, representing 42% of deaths attributable to *all* occupational risks[99]. The actual number of deaths may be higher considering the number of informal workers around the globe who are unaccounted for and endure high exposures with little to no protection or regulatory enforcement[76].

The informal electronic-waste (e-waste) recovery sector produces PM emissions from burning electronic wastes in open, surface fires in order to extract valuable metals. Typically lacking engineering controls or personal protective equipment (PPE) use, such e-waste workers experience occupational exposures diverse in their type, pathways and routes of exposure[14,78]. Sub-Saharan Africa is home to several of the world’s largest and most studied informal e-waste recovery sites[74]. At the Agbogbloshie e-waste site located in Ghana’s capital city Accra, workers and surrounding populations have high potential for exposure to e-waste associated pollutants[100].

The main methods used at Agbogbloshie for recovering reusable parts and metals from e-waste include manual dismantling and burning[8,20,26,75]. Dismantling methods, including pounding with hammers or similar devices, can release airborne chemical mixtures, potentially including heavy metals (e.g., Pb, Cd, Cr) and organic chemicals (e.g., brominated flame retardants (BFRs), and polychlorinated biphenyls (PCBs)) contained within electrical and electronic products. Burning e-waste, a simple and low cost way to remove plastic insulation and circuit boards, allowing copper and other metals to be retrieved, is performed at relatively low temperatures in open surface fires and often with non-traditional fuel sources (e.g., Styrofoam, discarded car tires). Aerosol and gas-phase emissions from burning e-waste and incomplete combustion include dioxins, furans, polycyclic aromatic hydrocarbons (PAHs), carbon monoxide, carbon, nitrogen oxides, sulfur dioxide and volatile organic compounds including formaldehyde[16]. PM from e-waste emissions may be of higher toxicity than PM from biomass fuel emissions and traffic-related emissions due to the high concentrations of industrial chemicals and metals in e-waste[101].

PM with an aerodynamic diameter $\leq$ 2.5 µm ($PM_{2.5}$) can readily reach the gas-exchange region of the lungs. Most of the coarse fraction ($PM_{2.5\text{-}10}$: 2.5 - 10 µm in aerodynamic diameter) is retained is deposited in the lungs' thoracic region. Health effects associated with PM sizes $\leq$ 10 µm in diameter include cancer and cardiovascular, respiratory and cerebrovascular morbidity and mortality [60,62]. Toxic constituents of PM from burning e-waste include persistent organic pollutants and heavy metals, known to be human carcinogens or to damage the central nervous, endocrine and/or reproductive systems[5].

Reported direct measures of air pollution at Agbogbloshie or other informal e-waste sites around the globe are limited. Caravanos et al. (2011) characterized personal inhalation among e-waste workers (n=5) at Agbogbloshie and found levels of Al (5.5 - 6.5 mg m^{-3}), Cu (1.2 mg m^{-3}), Fe (5.6 - 17.0 mg m^{-3}) and Pb (0.98 mg m^{-3}) which exceeded the American Conference of Governmental Industrial Hygienists (ACGIH) Threshold Limit Values (TLVs) of 1.0, 1.0, 5.0 and 0.05 mg/m^3, respectively[23]. Hogarh et al. (2018) measured atmospheric PCB concentrations at two Agbogbloshie locations and across sixteen other sites throughout Ghana; PCB concentrations at Agbogbloshie reached 11.1 ng m^{-3} in comparison to a median concentration of 0.48 ng m^{-3} across all other urban sites[40]. The authors concluded that burning practices at Agbogbloshie were a probable source of atmospheric PCBs across Accra[40].

In China, at the Guiyu informal e-waste site where burning e-waste is also performed , $PM_{2.5}$ concentrations from area samples ranged from 49.9 to 62.1 µg m^{-3}, exceeding concentrations in reference populations and China's national recommendations (24-hr mean $PM_{2.5}$ target: $\leq$ 35 µg m^{-3}) [43,102,103]. PM samples from the Guiyu e-waste site included high concentrations of heavy metals (including Pb and Cd), PAHs, and flame retardants [45–48,102,104]. Surrounding illegal e-waste sites in India, the mean PM_{10} concentration averaged over three months was 232.9 µg m^{-3} ($\pm$ 19.4); the authors also found the PM to contain high concentrations of Pb, Cu, Zn, Ni and Cr, which were mostly attributed to the burning of printed circuit boards[105]. Even in studies of formal electronic recycling facilities in Europe and the United States, which are typically licensed operations that should comply with occupational and environmental regulations, personal and indoor air quality samples found significant exposures to inhalable dust containing metallic pollutants, brominated flame retardants and organophosphate esters[78,106–108].

In our previous research at Agbogbloshie among the GeoHealth cohort (N=142), continuous measures of $PM_{2.5}$ (a total of 32,439 minutes) from the breathing zone of workers during 171 partial-shifts were found to be highest (mean: 203 µg m^{-3}) for workers burning e-waste[109]. Non-work-related activities, however, were also associated with exposure to unsafe concentrations of personal $PM_{2.5}$. For example, the mean personal $PM_{2.5}$ measured during eating and drinking was 80 µg m^{-3} [109]. Activity-specific exposure measures and estimates provide an opportunity for targeted risk-mitigating interventions among highly exposed worker groups. Characterizing inhalation exposures among workers may also shed light on potential environmental and health risks among communities living and working nearby, especially when prevailing wind direction places communities downwind from e-waste emission sources (e.g., burning). In Ghana, the contribution of emissions generated from e-waste recovery sources are not accounted for in predicted estimates of local or national ambient PM pollution[110].

In the Greater Accra region, there is a wide range of reported mean ambient $PM_{2.5}$ and PM_{10} concentrations (filter-based) in the existing literature; reported mean $PM_{2.5}$ concentrations range from 21 to 97 µg m^{-3} and from 57 to 144 µg m^{-3} for PM_{10}[111–113]. PM concentrations in Ghana are highest during the Harmattan season (November-February) when winds off the Saharan desert transport sand and dust across the region. Sources of ambient PM pollution in Ghana include crustal elements (especially during Harmattan winds), biomass burning, road dust and vehicular emissions, solid waste burning and sea salt [114,115]. The Ghana Environmental Protection Agency (EPA) has initiated a draft air quality management plan to achieve the World Health Organization's (WHO) recommendations (24-hour ambient $PM_{2.5}$ and PM_{10} targets: $\leq$25 and $\leq$ 50 µg m^{-3} respectively) [110,116]. Improved understanding of the contribution of e-waste recovery practices as a source of ambient PM pollution can inform air quality management. For example, apportioning sources of PM could help target mitigation efforts (e.g., elimination of e-waste burning practices).

The main objective is to compare relative levels of personal $PM_{2.5}$ and $PM_{2.5-10}$ exposures across work activities among e-waste recovery workers enrolled in the GeoHealth occupational cohort study in Accra, Ghana. Using a combination of continuous PM measures taken from worker breathing zones and time-activity data generated from wearable camera images, we estimate personal exposure by activity, adjusted for background levels of $PM_{2.5}$, study wave, day of the week, and meteorological variables. A second objective is to examine the empirical relationship between wind conditions and personal PM inhalation for workers positioned downwind and at the main source of PM emissions, the e-waste burning zones. Measures of the joint effects of activity and wind conditions on $PM_{2.5}$ and $PM_{2.5-10}$ are presented. Winds in Accra primarily arise from the S, W and SSW, causing plumes from burning e-waste to travel across the rest of the Agbogbloshie site and along the river where other workers and residents are located (see **Figure 1**). Assuming that plume rise will be low during conditions of high wind speed, we hypothesized that PM breathing zone concentrations would be high among dismantlers and other individuals who are typically located downwind of the emission source. With a shifting and meandering plume caused by low wind speeds and high variability in wind direction, we hypothesized that PM breathing zone concentrations would be high among burners who cannot move upwind of the emission source while tending the fires.

3.3 Methods

3.3.1 Study Sample

The GeoHealth occupational cohort study is an ongoing longitudinal study to assess environmental and occupational exposures and health effects among workers at the

Agbogbloshie e-waste site. Details on the worker population and recruitment procedure are presented elsewhere[109]. In brief, 142 e-waste workers were enrolled into the GeoHealth study during the first (March 14 - May 2 2017) or second (August 4 - October 16 2017) wave of data collection. Follow-up visits were scheduled for all participants during the second and third (January 8- April 20 2018) study waves. All study protocols were approved by the University of Ghana and University of Michigan Institutional Review Boards. Informed consent acquisition and data collection were conducted by trained, local interpreters in the participant's native or preferred language.

3.3.2 Background $PM_{2.5}$

Area monitoring of real-time ambient PM was conducted using a 5-channel optical particle counter (OPC) (Aerocet 831, Met One Instruments, Inc., OR, USA) at a fixed site approximately 6.5 meters above ground level and 1.35 km SSE of the Agbogbloshie e-waste site (see Figure 1). Given the prevailing S, W and SSW wind directions, this fixed monitoring site is primarily upwind of Agbogbloshie and is used as an approximation of "background" levels of $PM_{2.5}$, that is, levels unaffected by site activities. The OPC continuously measured per 1-minute concentrations of PM $\leq$ 1, 2.5, 4, and 10 µm in aerodynamic diameter and total suspended particulate (TSP) by converting particle counts into size-specific mass measurements (as µg m^{-3}). Continuous 1-minute data were averaged into hourly and daily measurements, on 50 days between June 2017 and February 2018. Hourly averages of PM_{10} that exceeded 2,000 µg m^{-3} (<1%) were considered potentially biased due to coincidence error (i.e., when multiple small particles appear as one larger particle resulting in an overestimate of large-channel particles) and censored. This decision was made based on user-experience with the device and a forthcoming analysis of agreement between OPC and gravimetric filter-based measurements collected at the same site[42]. Area monitoring did not occur during wave I (March 2017) due to problems establishing electricity service at the site. The surrounding land-use includes a four-lane road with intermittent traffic, rubbish collection and occasional biomass burning. As of mid-October 2017, after the site was established, changes in the surrounding land-uses were made, including intermittent fires and smoldering of excavated materials to the SE and W of the monitoring site[42]. Kwarteng et al. concluded that these changes rather than Harmattan dusts were likely responsible for strong elevations in observed PM levels during January and February 2018[42]. Although the location of the new PM source remained upwind of the e-waste site, PM concentrations recorded at the monitoring site after October 2017 were no longer representative of ambient PM air quality in Accra.

3.3.3 Personal PM

Continuous PM from the breathing zone of participants was measured using the same 5-channel OPC device as for area monitoring. $PM_{2.5-10}$ is derived by subtracting the fraction of PM $\leq$ 2.5 from PM $\leq$ 10 µm. Measures of PM_{10} that are potentially biased due to coincidence error (>2,000 µg m^{-3}) were censored; when aggregated to 15-minute averages, one observation needed to be censored. Sampling occurred on all days excluding Sundays and days with heavy precipitation. During Waves I and II, participants were asked to wear the backpack for 4 hours between 8AM and 4PM, in order to maximize the time during which workers were engaged in e-waste recovery activities. In wave III, the sampling duration was reduced to two hours to avoid damaging other equipment in the backpack during the Harmattan season. The sampling period averaged ($\pm$ standard deviation) 198 minutes ($\pm$ 83 minutes) across all three waves.

3.3.4 Job activities

Participant activities were recorded using a wearable, wide-angle GoPro Hero4© camera. The camera was attached to the forward-facing shoulder strap of the monitoring backpacks and, like the personal PM device, set to take one image every minute. Trained reviewers processed the time-stamped images using a data collection instrument designed specifically for the GeoHealth study with input from seasoned workers. Details on image processing and design of the data collection instrument are described elsewhere[109]. In summary, the instrument records the type and length of each activity which is comprised of one or more consecutive images and can be categorized either as a work-related (burning, dismantling, sorting/ loading, buying and selling, transporting and other), non-work-related (not actively working, smoking), or transportation-related activity (walking, bicycling, motorbike or car). "Not actively working" includes sub-categories of sitting, eating or drinking, cell phone use, prayer, and communicating with others. Reviewers identified images as "unusable" if it was clear from the image that the participant removed the camera and monitoring backpack from their body. Participant location during sampling was not recorded; however, objects identified in the images (e.g., tools, broken electronics, tires) were used to classify whether the participant was on or off the Agbogbloshie study site.

3.3.5 Meteorological Variables

Meteorological variables are measured at the Kotoka International Airport in Accra, located approximately 10.2 km NE of the Agbogbloshie e-waste site. Meteorological data are made publicly available by the National Oceanic and Atmospheric Administration's (NOAA) Integrated Surface Database (ISD) and the Global Historical Climatology Network (GHCN)[117–119]. Hourly temperature, visibility distance, dew-point, wind speed and direction and daily precipitation measured at the airport were obtained from the ISD and GHCN for the study period. Relative humidity was calculated from temperature and dew-point. In order to calculate a measure of wind direction variability (degrees) that corresponded to the hours during which personal monitoring took place (typically between 8AM and 4PM), the circular SD of the hourly wind direction measurements, which can assume values between 0 and 360 degrees, were used. Wind speed (m/s) was defined by averaging the hourly measures of wind speed (m/s) for the same sampling times. Two- and three-level categorical variables for both wind speed and wind direction were created; the two-level variable compared "high" (the upper fourth quartile (>75th percentile) with "low-medium" (the bottom three quartiles ($\leq$ 75th percentile); the three-level variable compared tertiles. Meteorological variables were used both as predictors of background $PM_{2.5}$ for days with missing measurements and as covariates in adjusted analyses. Packages used to process the meteorological data included "rnoaa", "openair", "humidity", and "circular" in RStudio[80].

3.3.6 Data management

A minute-by-minute database of image-based and time-specific activity logs for each worker was merged with the minute-by-minute, continuous PM data by participant ID, date and time. This database was used to create a 15-minute averaged database. The 15-minute averaging period reduced sampling noise and variability associated with 1-minute PM measurements and aligned with short-term exposure limits used in occupational settings, typically set at a minimum of 15-minutes. In addition, the average duration for all activity types exceeded 15 minutes, as described previously[109]. Each interval was assigned mean $PM_{2.5}$ and $PM_{2.5-10}$ concentration for the activity that was performed longest during the interval. In the rare event of a tie, the activity that occurred first was chosen. Time-intervals during which the camera and monitoring backpack were removed from the participant's body for the majority of the interval were excluded.

3.3.7 Statistical analyses

Descriptive statistics of the type and duration of activities performed by the participants were calculated. Given missing directly-measured background $PM_{2.5}$ data on several days during which personal sampling occurred, background $PM_{2.5}$ was estimated using a prediction model based on the observed background $PM_{2.5}$ data (N=50 days) from the upwind fixed site (approximately 1 km from Agbogbloshie) and meteorological variables measured at the airport (approximately 10.2 km from Agbogbloshie). The choice of predictors was based on a model described by O'Neill et al. (2002) for predicting ambient $PM_{2.5}$ in Mexico City using visibility distance and other meteorological variables typically available from local airports (O'Neill et al. 2002). The initial, full prediction model included: the extinction coefficient, a measure of "the total amount of light attenuated through adsorption and scattering by particles and gases" derived from visibility distance using the Koschmeider formula (Ozkaynak et al. 1985); temperature (minimum, maximum, and mean); relative humidity (minimum, maximum, and mean); dew-point (minimum, maximum, and mean); wind speed; and interaction terms between the extinction coefficient and temperature, and separately with relative humidity. Variable selection and predictions were performed using elastic net penalized linear regression with five-fold cross-validation ("glmnet" package in R). Predictions were based on the model whose tuning parameters gave a mean squared prediction error (MSPE) within one standard error of the minimum. Elastic net provides good prediction accuracy with a parsimonious model in the presence of correlated predictors and reduces the variance associated with ordinary least squares (OLS) estimators at the cost of introducing potential bias(Zou and Hastie 2005).

In two separate linear mixed models (see Equation 1), the changes in personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations associated with image-derived time-activity were estimated. Models accounted for the repeated measures design of the study and temporal autocorrelation in the 15-minute personal PM measurements by including random intercepts for participant-days and an auto-regressive (AR1) covariance matrix. *A priori* identified fixed effect covariates included background $PM_{2.5}$, study wave, day-of-week, temperature and relative humidity. To account for the non-linear relationship between personal inhalation exposure and temperature and relative humidity, thin-plate regression splines were used. Covariates were added to the model one at a time in order to examine their effect on the outcome. Improvements in model fit were assessed using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and R^2 calculated for a linear mixed model(Nakagawa, Johnson, and Schielzeth 2017). Conditional R^2, percent changes in $PM_{2.5}$ and $PM_{2.5\text{-}10}$ associated with an activity (exp (β) -1)* 100) and 95% confidence intervals (CIs) are presented. In sensitivity analysis, the final model was run without the AR(1) covariance matrix to evaluate the extent to which the association between change in personal PM exposure and change in activity could have been attenuated by over-controlling for temporal correlation.

Equation 1: Linear mixed model for estimating the association between activity and personal inhalation exposure to $PM_{2.5}$ and $PM_{2.5\text{-}10}$ in the GeoHealth study.

$$\begin{aligned} \ln(\boldsymbol{Personal\ PM})_{day,participant,time} &= \beta_0 + \beta_1 A\boldsymbol{ctivity}_{day,participant,time} + \beta_2 \boldsymbol{Covariates}_{day,participant} \\ &+ \delta(B\boldsymbol{ackground\ PM_{2.5}})_{day,participant} + S\big(\boldsymbol{Weather}_{day,participant,time}\big) + b_{day} + \tau_{participant} \\ &+ \varepsilon_{day,participant,time} \end{aligned} \tag{1}$$

$$b_{day} \sim N(0, \sigma_b^2)$$

$$\tau_{participant} \sim N(0, \sigma_\tau^2)$$

$$\varepsilon_{day,participant,time} \sim N(0, \Sigma)$$

$$\Sigma = AR(1) = cor\big(\varepsilon_{day,participant,time_1}, \varepsilon_{day,participant,time_2}\big) = \rho^{-|time_2 - time_1|}$$

Equation 1 legend: In this model, time is nested within participant, which is nested within sampling day. Activity includes not actively working (reference category), smoking, burning e-waste, sorting/loading e-waste, dismantling e-waste, transporting materials, buying/selling e-waste, and other (work-related) activities. The model is adjusted for covariates (study wave and day of week), background levels of $PM_{2.5}$, temperature and relative humidity. S() refers to a thin-plate smoothing spline, *b* is a random intercept for day, τ is a random intercept for participant, β and δ are regression coefficients, ε is a vector of random errors and AR(1) signifies the specified first order autoregressive covariance structure.

The joint effects of activity and wind conditions (direction and speed) on personal exposure to $PM_{2.5}$ and $PM_{2.5-10}$ were examined for a subset of participants who performed burning or dismantling activities. These activities were chosen because the locations of both are consistent over time and dismantling activities are downwind of the two burning zones (Figure 1). The hypothesized changes in personal PM concentrations among workers performing dismantling and burning e-waste activities according to different wind conditions are summarized in Figure 2, which reflect assumptions regarding plume dispersion. Due to the lack of available data, the influence of other factors that determine plume dispersion and rise (e.g. emission rate, mixing height, insolation, etc.) were not considered in this analysis.

Two-way interaction terms between activity and wind direction variability (low, medium and high) and activity and wind speed (low, medium and high) were added to the fully adjusted models. Although wind speed and direction are typically inversely correlated (i.e., high wind speeds are correlated with low variability in direction), our data showed only a modest correlation (correlation =-0.25). Therefore, the joint effects of wind speed and direction variability on the association between activity and personal inhalation exposure had to be examined in separate models in order to avoid small cell sizes and conserve statistical power. Main effects of the interaction model are presented graphically to facilitate their interpretation(Greene 2010). Additionally, effect modification results are presented, for two-level variables only, on the multiplicative and additive scale in a table following the recommendations provided by Knol and Vanderweele (2012) (Knol and VanderWeele 2012). “Super-additive” and “positive” multiplicative interaction are defined as changes in personal PM associated with the combined effect of activity and wind conditions that is larger than the sum and product, respectively, of changes associated with their individual effects.

3.4 Results

Among the 142 GeoHealth participants, 105 participants wore backpacks containing a camera and personal PM monitoring device. Participants with personal sampling did not differ from the full cohort across socio-demographic characteristics. During waves I, II and III, 51, 54 and 55 partial work shifts were sampled, respectively (N=160). The average length of shift samples per participant was 221, 214 and 160 minutes during waves I, II and III, respectively. A total of 2,110 15-minute intervals were averaged from a total of 31,650 minutes. Data from three participants collected on a day during wave I with a large urban fire adjacent to the Agbogbloshie e-waste site were excluded. Descriptive statistics on the GeoHealth cohort have been presented previously[109]. In brief, the all-male cohort is an average of 27 years old and reported working 6 to 7 days a week for an average of 10 hours per day (some of which is spent on-site, but not actively engaged in a work activity[109]).

3.4.1 PM and time-activity descriptive results

Descriptive results of time-activity and their corresponding levels of measured personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$, unadjusted for background levels, are shown in Table 1. The most common work activities were dismantling, sorting/ loading and burning (Table 1). For 50% of the recorded partial-shifts, workers were categorized as "not-actively working" (i.e., sitting, eating or drinking, cell phone use, prayer, and communicating with others). The average duration of activities ranged from 24 minutes (± 13) for walking to 80 minutes (± 90) for dismantling. Burning activities had the highest measured personal concentrations of both $PM_{2.5}$ (mean: 209 µg m^{-3}) and $PM_{2.5\text{-}10}$ (mean: 241 µg m^{-3}). Mean $PM_{2.5\text{-}10}$ concentrations were higher for transportation-related activities (131 µg m^{-3}) than for "other" activities (98 µg m^{-3}), but similar for $PM_{2.5}$.

3.4.2 Background $PM_{2.5}$

Observed background levels of $PM_{2.5}$ (N=50) from the upwind fixed site between June 2017 and February 2018 had an overall median and mean of 62 and 73 µg m^{-3} (± 53), respectively. During June through October (non-Harmattan season) 2017, the median was 34 µg m^{-3} (± 21); median levels increased to 80 µg m^{-3} (± 56) during November 2017 - February 2018 (Harmattan season). These observed values were used to predict missing daily averages of background $PM_{2.5}$ on days during which sampling took place (N=61). The prediction model with the minimum cross-validated MSE, which included as predictors visibility distance, minimum temperature, wind speed and an interaction between visibility distance and relative humidity, had an R^2 of 0.69 (Figure 3). Estimated background $PM_{2.5}$ concentrations for the study period had an overall median of 68 μg m^{-3} ($\pm$ 112), and median concentrations were 69 ($\pm$ 17), 61 ($\pm$ 7), and 76 ($\pm$ 140) μg m^{-3} for waves I, II and III, respectively. The correlation between observed and fitted values was poorest for low levels of $PM_{2.5}$. The poor correlation may be due to: the lack of observed background $PM_{2.5}$ measurements during the non-Harmattan season; lack of measurements during Wave I (March-April) when visibility distance (the main prediction variable in the model) was high; and/or that measurements taken after October 27, 2017 were elevated due to local fires located SE and W of the monitoring site.

3.4.3 Personal PM exposure for work and transportation-related activities

Changes in personal inhalation exposure to $PM_{2.5}$ and $PM_{2.5\text{-}10}$ associated with activity are presented in Table 2. The intercepts (67.3 and 97.4 μg m^{-3}, respectively) correspond to a 15-minute period of "not actively working", with all other covariates in the model, including background $PM_{2.5}$, wave of data collection, day of week, temperature and relative humidity, set to their reference levels (Table 2). Burning e-waste is associated with an adjusted personal $PM_{2.5}$ concentration of 86.3 μg m^{-3} (95% CI: 61.1, 121.9) or a 28.1% increase (95% CI: 10.7%, 48.2%) from levels when workers are not actively working. The presence of tobacco smoke is also associated with a large percent increase in $PM_{2.5}$ exposure (22.3%, 95% CI: 5.4%, 42.0%). Personal $PM_{2.5}$ exposures during walking, dismantling, sorting/loading, transporting materials, and bicycling activities are all moderately higher than exposure when not actively working (5.4-6.7%), resulting in adjusted mean personal PM concentrations that ranged from 71.0 to 71.9 μg m^{-3}. For $PM_{2.5\text{-}10}$, bicycling followed by motorbike use and burning are associated with the largest increases in personal exposure (45.7%, 30.7% and 28.1%, respectively) in comparison to not-actively working. However, unlike for $PM_{2.5}$, sharp differences in $PM_{2.5\text{-}10}$ between burning and the other work activities were not observed. Personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations were lower during Wave III (Harmattan season) in comparison to Wave I (non-Harmattan). Higher personal PM concentrations during Wave I in comparison to II and III may be due to the higher number of burning activities that were performed by the participants; in Wave I, 50 burning events were recorded in comparison to 32 during Waves II and III combined. Furthermore, it is unlikely that Harmattan winds contributed to personal or background PM measurements; out of a total of 27 days during which possible Harmattan dusts were identified using satellite data for the Dec 2017 – Feb 2018 period[42], only 7 of them overlapped with days of personal sampling. Among the days of the week, Mondays are associated with the highest, and Thursdays and Fridays with the lowest, concentrations of $PM_{2.5}$ and $PM_{2.5-10}$, although the confidence intervals are quite wide. Models run without accounting for temporal autocorrelation had similar results with respect to the rank order of associations between activities and personal PM exposure. However, the magnitude of the relative risks associated with each activity were larger, as expected.

3.4.4 Joint effects of activity and wind conditions on personal inhalation exposure

Figures 4 and 5 show wind conditions and the joint effects of activity and wind conditions on personal exposure to $PM_{2.5}$ and $PM_{2.5-10}$, adjusted for background $PM_{2.5}$, wave of data collection, day of week, temperature and relative humidity. Based on Kotoka weather station data from days and hours that coincided with personal monitoring (n=304 h), hourly wind speeds ranged from 1.0 to 10.3 m/s with an average of 5.2 m/s ($\pm$ 1.7), and winds originated predominantly from the S (25 %), W (24%) and SSW (20%) (Figure 4). Daily variation in wind direction ranged from 4.0 to 55.5 degrees with a mean and median of 26 degrees ($\pm$ 12). Throughout the sampling period, direction shifted from the W to the S and speed increased by approximately 1 m/s from the morning to late afternoon. Average wind speeds were highest during wave II and direction variability was highest during wave III (Figure 4).

Wind conditions modified inhalation exposures of dismantlers and burners (Figure 5). Personal $PM_{2.5}$ and $PM_{2.5-10}$ concentrations for burning activities increased with high wind direction variability. When plumes are expected to meander and their direction is harder to predict, burners may have greater difficulty avoiding the smoke (Figure 5, Plot A). Personal $PM_{2.5}$ exposure for burners was lowest during high wind speeds; however, a clear downward trend in $PM_{2.5}$ or $PM_{2.5-10}$ exposure associated with increasing wind speeds was not observed (Figure 5, Plot B). Personal $PM_{2.5-10}$, but not $PM_{2.5}$, for dismantling activities increased with wind speed (Figure 5, Plot B); entrainment of surface dust and particles generated during e-waste dismantling also may be contributing to $PM_{2.5-10}$ exposure. Dismantling activities were associated with higher concentrations of $PM_{2.5-10}$ than burning activities, except during periods of high wind variability.

Effect modification by wind conditions on personal $PM_{2.5}$ and $PM_{2.5-10}$ for participants exposed to burning e-waste in comparison to dismantling e-waste is presented in Table 3. The results provide preliminary evidence that high wind direction variability increases inhalation hazards among workers who are burning e-waste and high wind speeds increase inhalation hazards among those dismantling e-waste. For example, burning e-waste during conditions of high wind direction variability resulted in a 163.1% (95% CI: 81.7, 280.9) increase in personal $PM_{2.5}$ concentrations in comparison to a 32.3% (95% CI: -44.2, -17.9) decrease during conditions of low-medium wind variability. In other words, burners have higher PM exposures when the wind direction is variable. Evidence of a positive interactive relationship between burning e-waste and high wind direction variability was observed on the additive and multiplicative scales for both $PM_{2.5}$ and $PM_{2.5-10}$. The alternative negative interaction between burning e-waste and high wind speeds for $PM_{2.5}$ and $PM_{2.5-10}$ (i.e., a decrease in exposure for burners when wind speeds are high) was also observed on both the additive and multiplicative scales. For dismantlers, personal $PM_{2.5}$ and $PM_{2.5-10}$ exposure increased by 28.6% (95% CI: -13.1, 89.8) and 12.0% (95% CI: -25.0, 67.2), respectively, during high wind speeds in comparison to low and medium speeds; however, the results were not statistically significant at the 0.05 alpha level (Table 3).

3.5 Discussion

3.5.1 *Main findings*

This study contributes to the limited data on inhalation exposure among e-waste workers, identifies highly exposed worker groups by work activity, and contributes to our understanding of sources and causes of exposure among these workers. The mean $PM_{2.5}$ (80.2 $\mu g\ m^{-3}$) and $PM_{2.5-10}$ (123.2 $\mu g\ m^{-3}$) concentrations measured in the breathing zone of e-waste workers at the Agbogbloshie site in Accra, Ghana considerably exceed the existing WHO $PM_{2.5}$ and PM_{10} ambient air quality guidelines. Image-based time-activity data helped establish differences in personal PM by specific activity; during 15-minutes of burning e-waste activities, personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations increased from background levels on the site by 28.1% and 30.7%, respectively. Although burning e-waste exceeded any other activity's $PM_{2.5}$ concentrations, the concentrations of $PM_{2.5\text{-}10}$ during burning were similar in magnitude to measured concentrations that occurred during transportation-related activities (bicycling or motorbike and car use). Our analysis of associations between activity and personal inhalation exposure by wind conditions strongly suggest that, in the setting in Agbogbloshie, plumes from burning e-waste are a source of PM exposure for downwind workers, and that with more variable winds, workers performing the burning activities are unable to avoid smoke exposure, leading to peak exposures among these workers.

3.5.2 *$PM_{2.5}$ and $PM_{2.5\text{-}10}$ breathing zone concentrations by job activity*

Higher personal $PM_{2.5}$ concentrations during burning activities and higher $PM_{2.5\text{-}10}$ exposures during transportation-related activities in comparison to periods during which e-waste workers were not actively working were as expected. Personal $PM_{2.5}$ concentrations were similar among walking, transporting, sorting/ loading and dismantling activities, possibly because these activities occur in close proximity to one another and in areas unprotected from smoke associated with burning. At Agbogbloshie, workers transport materials by foot between the e-waste processing area and the burning zones using carts and wheelbarrows. Buying and selling activities were associated with the lowest levels of $PM_{2.5}$ and $PM_{2.5\text{-}10}$; buyers and sellers typically have higher incomes and sit in sheds, some of which have fans, removed from the burning zones. Activities that occur mostly off-site, including bicycling and motorbike use, were associated with higher levels of $PM_{2.5\text{-}10}$ concentrations. This coarse PM fraction likely includes road dust and PM emissions from old vehicles.

3.5.3 *Local dispersion from e-waste burn pits*

Wind direction and wind speed represent two factors involved in dispersion, transport and transformation of e-waste emissions. Additional factors influencing plume trajectory, plume rise and dilution include parameters related to the emission's source (e.g., type, size, number, emission rate, heat flux), additional meteorological and micrometeorological factors (e.g., cloud cover, insolation, humidity, temperature, lapse rate and inversions, mixing height), and orographic and topographical factors (e.g., surface roughness, surrounding building heights, and land/water interfaces).

Emissions from open e-waste burning at Agbogbloshie are a ground-level area source. Considering the S, W and SSW prevailing winds that occurred during sampling hours, most workers are at a downwind distance of 200 to 400 m and a crosswind distance of less than 300 m from the plume centerline. Other than the location of the emission source, the number of fires, their size, the type of accelerants used and materials burned, much less the emission rate and temperature, are unknown, and many of these factors will change on a daily or hourly basis. Agbogbloshie has a relatively flat terrain with the highest structures being small sheds and mosques (approximately 5 m tall), and the adjoining lagoon, drainage canal and terrain have limited relief (approximately 10 m). The Gulf of Guinea coastline is approximately 3 km away, far enough to limit some effects associated with land-sea interfaces.

Local exposure to workers downwind of the burning area depends on the fire's emission rate, plume rise, dispersion, and other factors, which can all be affected by winds. As depicted in Figure 2, with high wind speeds, plume rise may be very limited and the plume is essentially at or near ground level, thus increasing the potential for exposure among e-waste workers downwind. High wind speeds and low variability in direction may also increase the burning rate, potentially increasing emissions, or alternatively diluting the plume. In any event, workers who are burning waste under such conditions are able to stay upwind and thus decrease their exposure. Anecdotal and photographic evidence from the wearable cameras demonstrates how burners avoid smoke exposure by modifying the location of their fires on days with steady and strong winds. However, if winds are meandering and plume rise is limited or non-existent (likely with lower temperature, dispersed or smoldering fires), then wind shifts may cause dispersion in multiple directions causing exposures among burners to vary from low to high. Workers further downwind and over a wide swath of the e-waste recovery site will also be exposed. Low wind speeds, however, also have countervailing effects: with a sufficiently large and hot fire, plume rise will increase with low speeds, and pollutants will be transported well above the breathing zone of workers, leading to relatively low exposure on-site. At the urban scale, i.e., considering off-site exposure in Accra, even elevated plumes will contribute to exposure, although the maximum effects may be experienced at a further distance and concentrations will be lower. Still, e-waste burning may add to the PM exposure experienced by Accra residents. Such trends and diurnal emission patterns may be quantified by dispersion models such as U.S. Environmental Protection Agency's (EPA) SCREEN View[126]. However, additional information regarding emission rates and other parameters are needed to implement these models.

3.5.4 Toxicity of particulate matter generated from e-waste

The concentrations of personal $PM_{2.5}$ and $PM_{2.5-10}$ exposure among these e-waste workers far exceed ambient air quality guidelines. However, they do not exceed the permissible exposure limit (PEL) for "otherwise unregulated" particulates defined by the U.S. Occupational Health and Safety Administration (OSHA) (15 mg m^{-3} for total particulate and 5 mg m^{-3} for the respirable fraction)[127]. However, personal protective equipment, e.g., masks or respirators, would typically be utilized to minimize exposure with such PM levels. PM emissions from burning e-waste are comprised of highly toxic constituents. In air samples of TSP and $PM_{2.5}$ from the Guiyu e-waste site in China, concentrations of PAHs, dioxins, flame retardants and metals (e.g., Cr, Zn, Cu, Pb, and As) were higher when compared with urban and rural regions[102,104,128]. Cesaro et al. (2019) modelled the chemical reactions that occur during open e-waste burning and found that the potential hazards from open burning of cables made of copper, thermoplastic elastomers, polyvinyl chloride, and polyethylene foils were higher than for computer and mobile printed circuit boards, and above the threshold limit values[101]. This result was driven by the high content of chlorine-containing plastics in cables that generate dioxin (specifically, 2,3,7,8-tetrachlorodibenzo-p-dioxin)[101]. Exposure to high concentrations of metals and persistent organic pollutants may result in more severe and varied health effects than those associated with unregulated particulate (e.g., corn dust), traffic-related and ambient sources of PM air pollution.

3.5.5 Implications, interventions, and policy options

Key findings of the current study, on a site where open burning is routinely used to recover metals from e-waste, and other workers dismantling e-waste are typically located downwind of burning sites given prevailing wind patterns, that a combination of wind speed and variability in wind direction are highly predictive of personal exposures to particulate, provide a previously unreported type of objective data reinforcing the view that open burning is a critical source of potentially toxic exposures to workers. Given this context, interventions aimed at reducing personal inhalation exposures among e-waste workers should focus on burning activities as the primary PM emission source affecting essentially all workers on the site. Other activities, such as dismantling and pounding e-waste and draining of oils, are also problematic and should be addressed by hazard reduction strategies. Many of the existing interventions utilized at informal e-waste sites around the globe, such as educational campaigns, training, and distribution of PPE provide minimal protection on their own and have not provided economic incentives for the workers. Effective engineering solutions should be designed with input from the workers, and improve efficiency and the capture of raw materials. Interventions at Agbogbloshie or other e-waste recovery sites have the difficult challenge of balancing pollution controls with job availability. Ongoing monitoring of exposure and worker's health is recommended to help validate the effectiveness of an intervention. A hierarchy of strategies aimed at air pollution prevention, their opportunities and potential challenges specific to Agbogbloshie and other informal e-waste sites is shown in Table 4 [129–131].

The creation of informal and formal sector partnerships is a proposed solution to eliminate environmental exposures from informal e-waste recovery[132]. Under this scenario, informal recyclers collect, dismantle, and repair e-waste, while formal sector facilities, subject to occupational and environmental regulations, perform raw material recovery and waste disposal. Although this model has strong potential to reduce occupational and environmental exposures in settings like Agbogbloshie, it may not be sustainable if the earnings among informal workers are reduced through their loss of control of the final product. Strong regulatory oversight is also needed to ensure safe conditions in the formal facilities.

On a national scale, a variety of Extended Producer Responsibility (EPR) policies for e-waste management have been implemented in the European Union (EU), Switzerland, Japan, and parts of the United States and Canada[4,133]. An EPR policy approach extends the responsibility to take back used products to the manufacturer. Different management approaches and take-back schemes have resulted in varying degrees of compliance and collection efficiency[133]. A 2011

EU directive placed further restrictions on the use of hazardous substances in the design of electronic and electrical equipment[133]. India and Thailand have also drafted e-waste management regulations. However, black markets and the large informal recycling sectors that do not fall under the regulation's jurisdiction are limiting factors of such policies that are yet to be overcome[133]. In countries such as Ghana with large informal recycling sectors, a different set of management principles sensitive to the local social, cultural, political, and economic tapestry is needed.

3.5.6 Strengths and limitations

A strength of this research is the unique and highly time-resolved data on personal inhalation exposure to $PM_{2.5}$ and $PM_{2.5\text{-}10}$ in combination with photo-validated time-activity data among informal e-waste workers. The use of available airport weather data to estimate background levels of $PM_{2.5}$ in a place where directly measured concentrations are not readily available can be replicated in other studies with the same data limitations. Comparisons of breathing zone PM concentrations by activity helped identify burning e-waste and transportation-related activities as the greatest sources of personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$, respectively. Examining the joint effects of activity and wind conditions on personal inhalation exposure provided a useful step in understanding whether and how emissions from burning e-waste contribute to personal inhalation among different groups of workers. Another strength is that we suggested air pollution control strategies viable in LMIC settings.

Optical measurements of size-specific personal PM concentrations are limited in that they can diverge from gravimetric (e.g., filter-based) mass measurements, considered the reference approach. Optical measurements can be affected by particle characteristics, instrument response, inlet and sampling configurations, and humidity, and thus site-specific correction factors are often recommended. Based on a related study at the Agbogbloshie site where both optical measurements (using the same instrument as in the present study) and gravimetric measurements were collected at fixed monitoring sites, optical $PM_{2.5}$ measurements were biased downwards by 21% from gravimetric measurements (Kwarteng et al. 2020). The backpack samplers, however, differed from the tested configuration in that the sampling inlet on the chest strap was connected to the instrument in the backpack using a length of tubing.

Numerical and field experiments conducted to understand penetration through the tubing indicated losses of up to 19% for $PM_{2.5}$ and 23% for $PM_{2.5-10}$. These preliminary results suggest that PM concentrations reported in this paper may be underestimated. However, this would not change comparisons of relative exposure concentrations by activity since these biases scale across all measurements in the study, regardless of the activity.

Data screening was used to exclude other biases. Half (n=13) of the observations exceeding the Aerocet optical device's maximum concentration range (1000 $\mu g\ m^{-3}$ as stated by the manufacturer) occurred during burning e-waste activities. By censoring measurements exceeding 2000 $\mu g/m^3$, the most severe cases of bias due to coincidence error were avoided. In a sensitivity analysis, our main results did not differ after censoring values exceeding 1000 $\mu g\ m^{-3}$. The lower cut-off, however, would have the effect of underestimating concentrations for activities associated with high PM exposures.

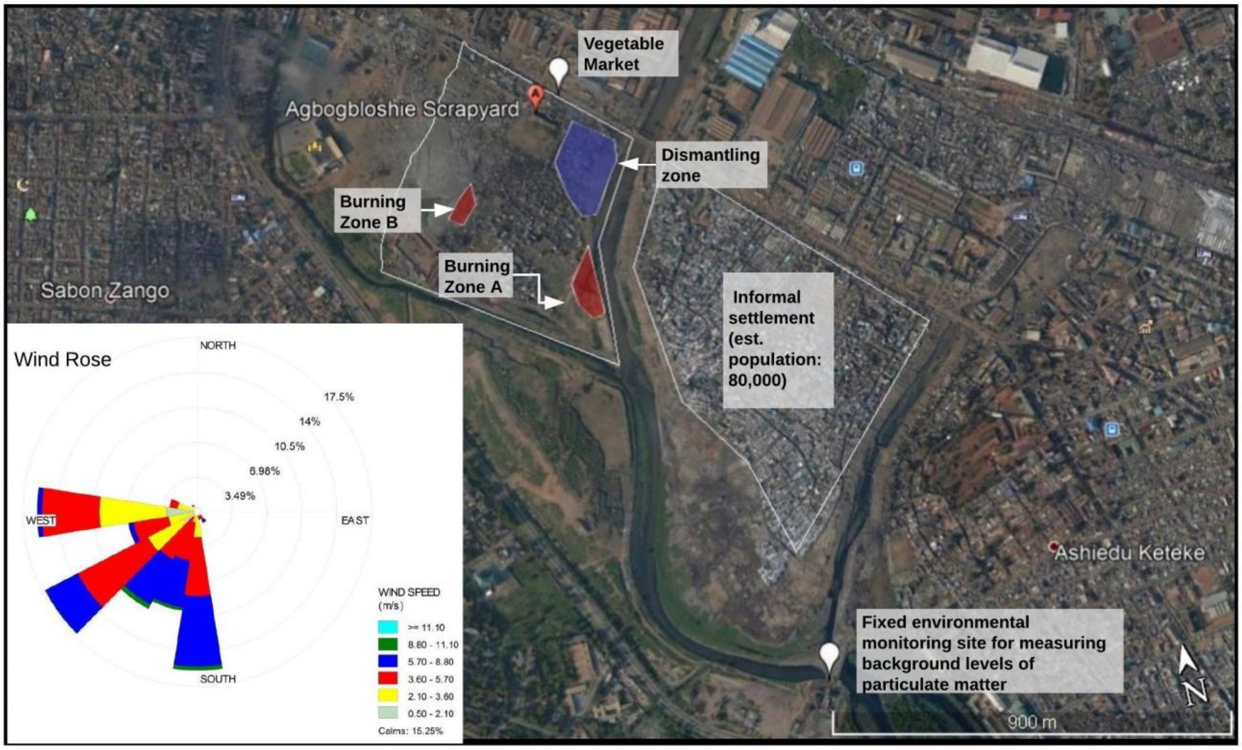
Models were adjusted for fitted rather than observed measures of background $PM_{2.5}$. Unknown measurement error may have resulted in an over- or underestimate of fitted background $PM_{2.5}$ values. Overestimates of background $PM_{2.5}$ may have occurred due to the lack of observed background $PM_{2.5}$ observations from Wave I of the study during the non-Harmattan season and elevations in observed background $PM_{2.5}$ concentrations after October 26, 2017 due to changes in land-use (e.g. smoldering excavation materials) near the monitoring site. Adjusting for such over- or under-estimates of background $PM_{2.5}$ in the statistical models might falsely reduce or enlarge, respectively, the estimated proportion of PM from occupational sources. In a sensitivity analysis stratified by wave, the moderate associations between personal PM (both sizes) and background $PM_{2.5}$, was highest during wave 1, followed by waves 3 and 2; however, when using an interaction term between background $PM_{2.5}$ and study wave, the differences by wave did not reach statistical significance. Similarly, in models unadjusted for background $PM_{2.5}$, the associations between personal PM (both sizes) and activities did not change significantly. Evidence on the joint effect of wind conditions and activity on personal inhalation exposure relied on measures of wind speed and direction from the Kotoka International airport, which may not have accurately represented the microclimate at Agbogbloshie. Agbogbloshie has slightly lower wind speeds and more variable wind directions than the the Kotoka airport location (Kwarteng et al. 2020). Lastly, we were unable to account for potential non-work related sources of personal PM exposure outside of the camera's view (e.g. nearby cooking, gravel road traffic and diurnal changes).

3.5.7 Conclusions

The greatest reductions in personal exposures for all e-waste workers will likely come from the replacement of current burning practices with the development of a safer and more efficient method of metal extraction viable in low and middle-income countries. Our preliminary evidence suggests that burning activities not only result in elevated personal PM concentrations for those performing the activity, but also contribute to elevations in personal $PM_{2.5}$ and $PM_{2.5-10}$ concentrations among downwind workers who are performing different tasks. Reducing the amount of time that workers spend on the site without actively working (50% of the monitored work-shifts in this sample) could reduce unnecessary exposure to occupational sources of PM, among other pollutants with high toxicity; however, with the knowledge that many of the workers live on site out of necessity, this is not a feasible reality without substantial and long-term structural changes in Accra. Development and implementation of air pollution control strategies requires a collaborative effort among diverse stakeholders, including workers, engineers, industry, government, academia and local organizations in order to overcome the many challenges in designing effective interventions for an informal work site characterized by lack of innovative engineering solutions, economic capital and technically trained workers. Effective interventions will balance the reduction of occupational and environmental exposures with the maintenance of job availability for workers who depend on e-waste recovery for their livelihoods.

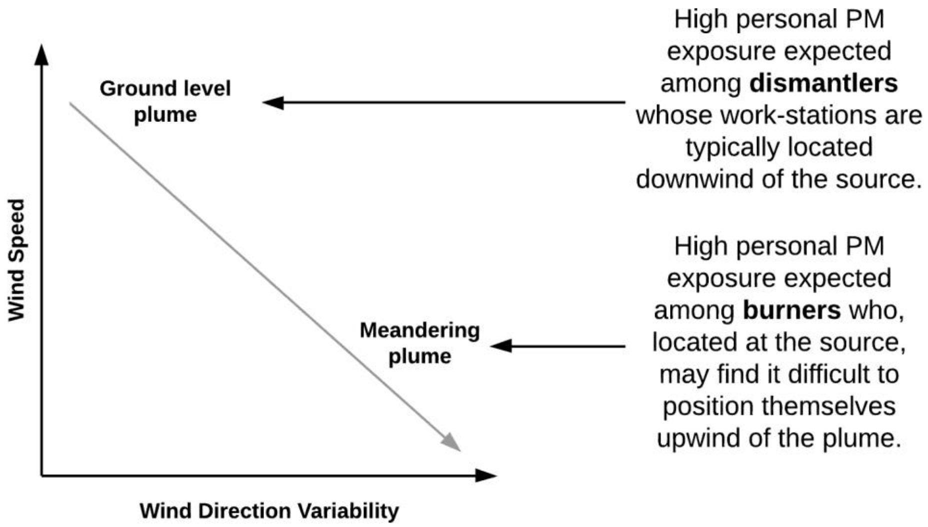
3.6 Figures

Figure 3-1: Map of the Agbogbloshie scrap and e-waste recovery site and surrounding area.



Legend: The Agbogbloshie site is approximately 0.5 km^2 in area. The highlighted polygons indicate the main zones where e-waste burning takes place: "Burning Zone A" and a secondary, smaller and newer burning zone "Burning Zone B", and the dismantling zone where most e-waste processing occurs (e.g., sorting, loading, weighing). Pins indicate locations of the fixed environmental monitoring station for background levels of $PM_{2.5}$, and the adjacent vegetable market. The wind rose (date range: 1/1/2017- 5/1/2018, timeframe: 8AM – 4PM) shows that prevailing winds during the timeframe of personal sampling originated primarily from the S, W and SSW. Map created using Google Earth Pro V 7.3.$_{2.5}$776. (10/7/2015). © Google 2018. Wind rose created by WRPLOT View (ver. 8.0.2) provided by Lakes Environmental.

Figure 3-2: Hypothesized effects of wind speed and direction variability on PM exposure among workers performing dismantling and burning activities at Agbogbloshie electronic waste recovery site, Accra, Ghana.

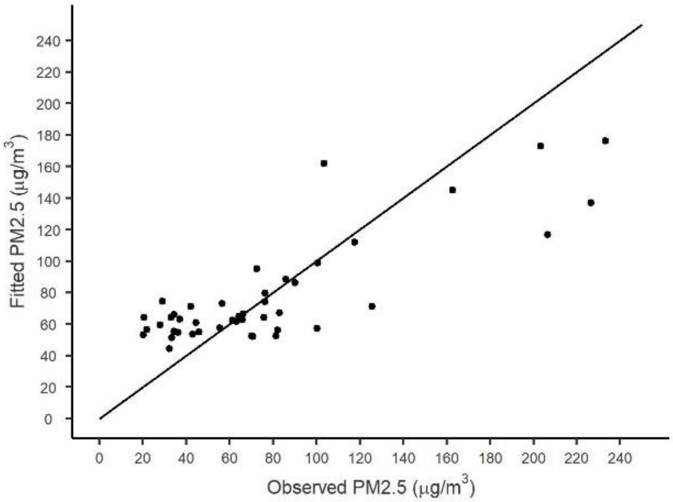


High personal PM exposure expected among **dismantlers** whose work-stations are typically located downwind of the source.

High personal PM exposure expected among **burners** who, located at the source, may find it difficult to position themselves upwind of the plume.

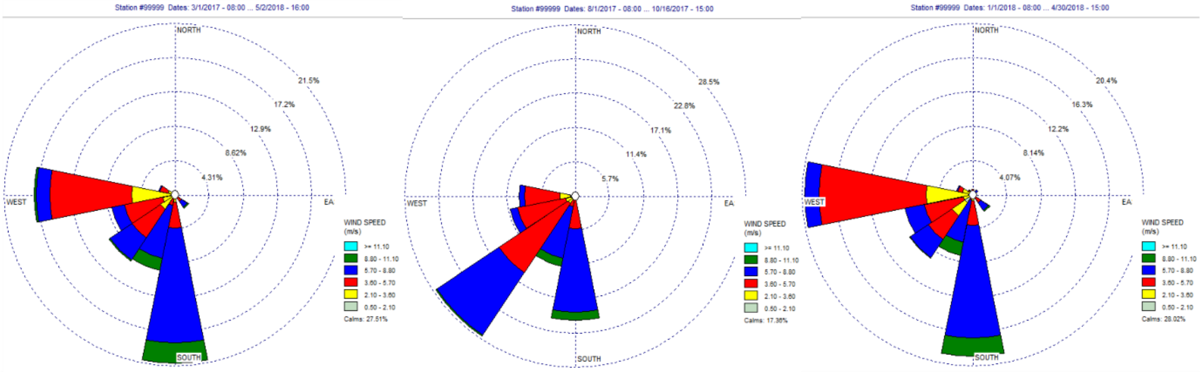
Legend: During conditions of low wind direction variability, which typically occur during periods of high wind speeds, a ground level plume stemming from the e-waste burn pits is expected. Alternatively, a meandering plume is likely to results during periods of high wind direction variability and low wind speeds. The hypothesized changes in personal PM concentrations for workers positioned at the burn pits (“burners”) and downwind of the burn pits (“dismantlers”) during each of these plume types are described.

Figure 3-3: Correlation between fitted and observed background PM$_{2.5}$ measured between June 2017 and February 2018.



Legend: Observed concentrations of background PM$_{2.5}$ were measured at a fixed site 1.35 km upwind of the Agbogbloshie e-waste site on 50 days between June 2017 and February 2018. Variable selection and predictions were performed using elastic-net penalized linear regression. Models were adjusted for visibility distance, temperature, wind speed and an interaction term between visibility distance and relative humidity.

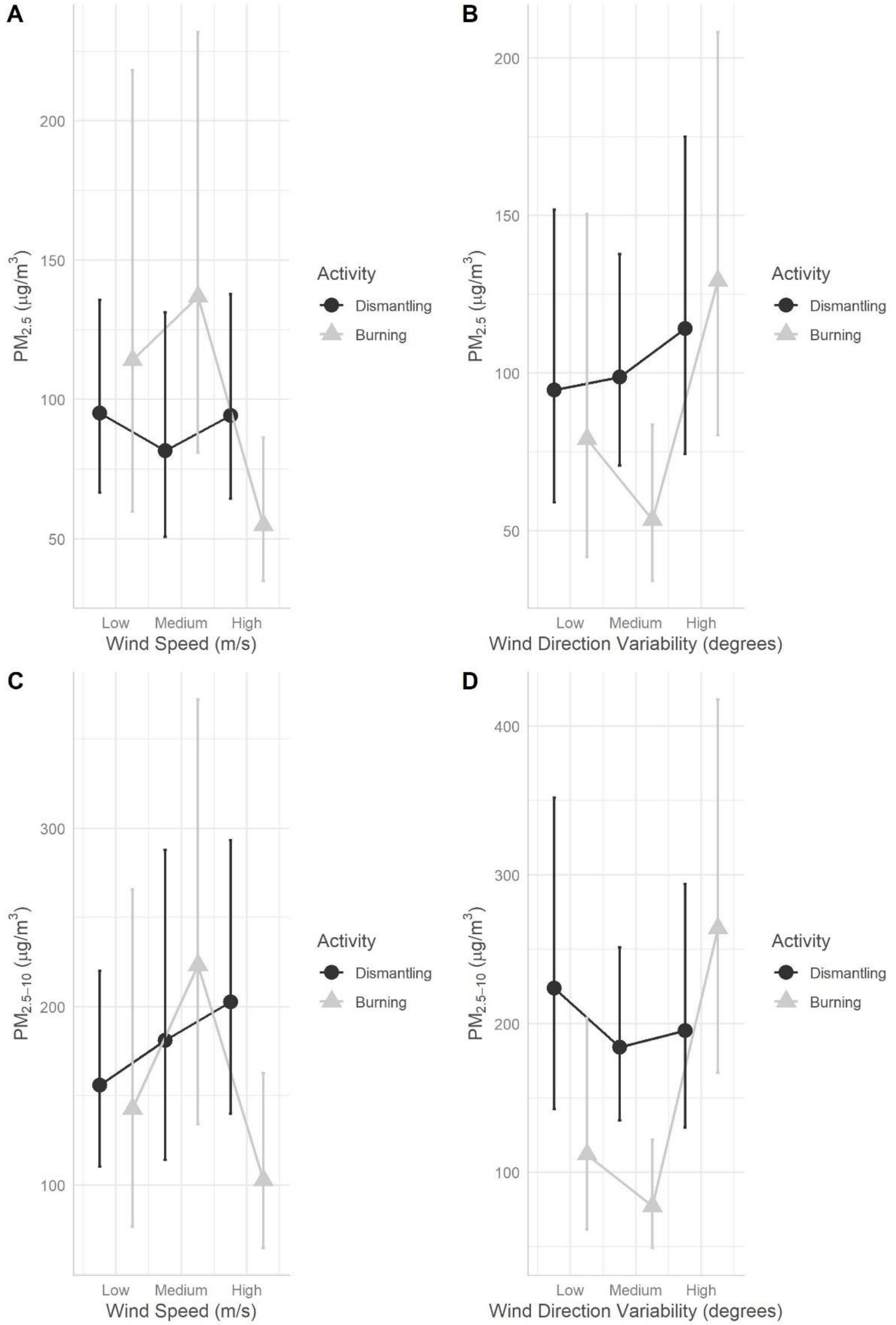
Figure 3-4: Wind roses from Kotoka International Airport by wave of data collection, 2017-2018.



WAVE I (MARCH 14 - APRIL 02 2017) **WAVE II (AUGUST 04 - OCTOBER 16 2017)** **WAVE III (JANUARY 08 - APRIL 20 2018)**

Legend: The wind roses for study wave I, II and III show that prevailing winds originated primarily from the S, SW and W, respectively. Wind rose were created by WRPLOT View (ver. 8.0.2) provided by Lakes Environmental.

Figure 3-5: Marginal effects of a change in activity and wind conditions on the predicted means of personal $PM_{2.5}$ (plots A and B) and $PM_{2.5\text{-}10}$ (plots C and D) exposure among e-waste workers, Agbogbloshie, Accra, Ghana, 2017-2018, (n=381).



Caption: Wind speed (plots A and C) cut-points are derived from the 33rd (4.6 m/s) and 66th (5.7 m/s) percentiles. Wind direction variability (plots B and D) cut-points for “Low”, “Medium”, and “High” are derived from cut-points at the 33rd (20.1 degrees) and 66th (30.2 degrees) percentiles. Marginal effects represent the expected change in personal exposure to $PM_{2.5}$ and $PM_{2.5-10}$ as a function of a change in activity and wind conditions while holding all other variables constant. Models were adjusted for background $PM_{2.5}$, study wave, day of the week, temperature and relative humidity. Error bars represent 95% confidence intervals.

3.7 Tables

Table 3-1: Time-activity and personal inhalation exposure to particulate matter averaged over fifteen minute intervals among 105 electronic-waste workers at Agbogbloshie e-waste recovery site, Accra, Ghana, 2017-2018.

		Activity Frequency		PM$_{2.5}$ (µg m^{-3})		PM$_{2.5-10}$ (µg m^{-3})	
	Activity Type	Mean length of activity in minutes ± SD	Total minutes during which activity was performed (%)	Mean ± SD	Median (Range)	Mean ± SD	Median (Range)
Work-Related		57 ± 64	8955 (28)	100.1 ± 130.2	66.1 (12.2, 1150.6)	166.5 ± 190.3	105.9 (9.5, 1702.8)
	Dismantling	80 ± 90	4485 (14)	90.0 ± 81.9	68.7 (13.4, 683.1)	145.9 ± 132.9	102.9 (17.7, 1101.7)
	Sorting, loading	45 ± 45	1530 (5)	81.4 ± 45.0	69.1 (14.4, 312.3)	169.4 ± 186.0	101.2 (23.7, 1000.8)
	Transporting materials	33 ± 25	825 (3)	71.4 ± 54.3	50.6 (18.2, 271.3)	160.5 ± 154.4	105.9 (22.5, 721.2)
	Burning	59 ± 44	1230 (4)	208.6 ± 283.2	71.7 (23.7, 1150.6)	240.9 ± 341.0	104.7 (22.0, 1702.8)
	Buying, selling, weighing	29 ± 18	315 (1)	58.9 ± 48.5	58.6 (12.2, 191.0)	161.9 ± 161.8	130.0 (9.5, 580.6)
	Other (Work)	52 ± 30	570 (2)	59.5 ± 23.3	58.1 (19.4, 121.1)	172.5 ± 164.9	126.5 (14.9, 858.5)
Transportation-Related		26 ± 17	5655 (18)	72.9 ± 46.0	62.0 (3.4, 468.0)	130.8 ± 124.2	100.0 (9.8, 1173.1)
	Walking	24 ± 13	4020 (13)	78.6 ± 49.6	66.5 (3.4, 468.0)	126.2 ± 122.3	98.9 (9.8, 1173.1)
	Motorbike or Car	31 ± 30	1155 (4)	57.2 ± 33.5	50.9 (16.3, 180.1)	145.6 ± 143.7	100.8 (12.5, 581.9)
	Bicycling	30 ± 11	480 (2)	62.5 ± 27.5	54.8 (15.9, 148.6)	132.9 ± 82.7	124.7 (23.2, 370.0)
Other		71 ± 78	16980 (54)	72.2 ± 47.9	64.3 (3.9, 558.2)	97.9 ± 100.0	71.1 (9.0, 1197.9)
	Not actively working[a]	74 ± 80	15915 (50)	71.1 ± 47.4	63.2 (3.9, 558.2)	99.5 ± 102.5	71.1 (9.0, 1197.9)
	Smoking	46 ± 48	1065 (3)	87.7 ± 52.1	78.0 (10.8, 253.1)	74.1 ± 44.8	70.7 (12.9, 238.3)
Total		51 ± 62	31590 (100)	80.2 ± 81.0	64.4 (3.4, 1150.6)	123.2 ± 138.8	83.5 (9.0, 1702.8)

Note: Activity type and length were derived from wearable cameras and continuous size-specific personal inhalation concentrations were measured using an optical device. Summaries are calculated from a grand total of 31,650 minutes (n=2,110 15-minute intervals), 60 minutes were "unusable" because the participant removed the camera and backpack with optical device for measuring PM during sampling. SD, standard deviation.

[a] "Not actively working" includes activities of sitting, eating or drinking, cell phone use, prayer, and communicating with others

Table 3-2: Estimated adjusted personal exposure and percent change in personal exposure to $PM_{2.5}$ and $PM_{2.5-10}$ by work and transportation-related activities in comparison to non-work related activities among 160 work shifts from 105 electronic-waste recovery workers, Agbogbloshie, Accra, Ghana, 2017-2018.

		$PM_{2.5}$		$PM_{2.5-10}$	
		Conditional R^2: 0.47	Adjusted	Conditional R^2: 0.51	Adjusted
Exposure and covariates	Period of exposure	% change in personal exposure (95% CI)[a]	estimated concentration (95% CI)	% change in personal exposure (95% CI) [a]	estimated concentration (95% CI) [a]
Intercept	15-minute	N/A	67.3 (54.9, 82.5)	N/A	97.4 (73.0, 129.9)
Activity (reference = Not actively working)[c]					
Burning	15-minute	28.1 (10.7, 48.2)	86.3 (61.1, 121.9)	30.7 (10.1, 55.1)	127.5 (81.2, 202.1)
Presence of tobacco smoke	15-minute	22.3 (5.4, 42.0)	82.4 (58.1, 116.9)	-2.1 (-17.9, 16.6)	95.4 (60.5, 152.0)
Walking	15-minute	6.7 (0.3, 13.4)	71.9 (55.3, 93.3)	16.2 (8.2, 24.8)	113.4 (79.8, 162.7)
Dismantling	15-minute	5.9 (-3.8, 16.5)	71.3 (53.1, 95.9)	19.2 (6.4, 33.5)	116.2 (78.4, 174.0)
Sorting, Loading	15-minute	6.3 (-5.6, 19.7)	71.6 (52.1, 98.5)	15.6 (0.6, 32.9)	112.8 (74.2, 173.2)
Transporting materials	15-minute	6.4 (-7.9, 23.1)	71.7 (50.8, 101.2)	20.1 (1.4, 42.2)	117.1 (74.7, 185.4)
Bicycling	15-minute	5.4 (-11.7, 25.9)	71.0 (48.7, 103.6)	45.7 (18.5, 79.2)	142.1 (87.4, 233.5)
Motorbike or Car	15-minute	-2.0 (-13.2, 10.5)	66.0 (47.9, 90.9)	28.1 (11.3, 47.5)	124.9 (82.0, 192.2)
Buying, selling, weighing	15-minute	1.0 (-18.9, 25.7)	68.0 (44.7, 103.4)	7.7 (-16.6, 39.)	105.0 (61.5, 181.1)
Other (Work)	15-minute	-10.4 (-26.7, 9.6)	60.4 (40.4, 90.1)	-4.6 (-24.7, 20.9)	93.1 (55.5, 157.5)
Background $PM_{2.5}$ ($\mu g\ m^{-3}$) (reference= mean)	24-hour	0.5 (0.2, 0.8)	67.7 (55.2, 82.9)	0.8 (0.4, 1.3)	98.3 (74.0, 132.0)
Wave (reference = wave I (non-Harmattan))					122.3 (80.5, 191.4)
Wave II (non-Harmattan)	Aug-0ct	-30.6 (-44.0, -13.9)	46.8 (30.9, 70.9)	-46.5 (-60.3, -27.9)	52.2 (29.3, 93.9)
Wave III (Harmattan)	Jan- April	-27.6 (-42.5, -8.7)	48.8 (31.7, 75.1)	-38.3 (-55.5, -14.3)	60.2 (32.8, 111.7)
Day of the Week (reference = Friday)[c]					
Monday	day	46.9 (13.7, 89.6)	98.9 (62.7, 156.0)	42.4 (-1.4, 105.5)	138.8 (72.7, 267.8)
Tuesday	day	11.5 (-12.1, 41.4)	75.1 (48.5, 116.3)	16.8 (-17.0, 64.3)	113.9 (61.2, 214.1)

Wednesday	day	18.6 (-6.3, 50.1)	79.9 (51.7, 123.5)	18.2 (-15.5, 65.6)	115.3 (62.2, 215.8)
Thursday	day	-0.4 (-21.4, 26.3)	67.1 (43.3, 103.9)	3.6 (-26.3, 45.7)	101.0 (54.3, 189.8)
Saturday	day	25.9 (-8.1, 72.7)	84.8 (50.7, 142.)	14.3 (-27.3, 79.5)	111.4 (53.6, 233.9)

Note: All estimates are from linear mixed effect models adjusted for background $PM_{2.5}$, study wave, day of week, temperature and relative humidity.

[a] Percent change calculated by (exp (β) -1)* 100;

[b] "Not actively working" includes activities of sitting, eating or drinking, cell phone use, prayer, and communicating with others;

[c] Sampling occurred on all days excluding Sunday.

Table 3-3: Percent change in exposure to PM$_{2.5}$ (A) and PM$_{2.5\text{-}10}$ (B) by joint effect of wind conditions and activity type among 381 e-waste recovery workers at the Agbogbloshie site in Accra, Ghana, 2017-2018

(A) Exposure to PM$_{2.5}$

		Dismantler (n=299)		Burner (n=82)		Burners v. dismantlers within strata of wind	Measure of effect modification on multiplicative scale[a]	Measure of effect modification on additive scale[b]
Effect modifier		N	% change (95% CI)[d]	N	% change (95% CI)	% change (95% CI)	% change (95% CI) of interaction term	RERI (95% CI)[c]
Wind direction variability	Low-Med[e] (0-34°)	252	REF	47	-38.8 (-53.8, -19.0)	-32.3 (-44.2, -17.9)	280.7 (87.4 , 673.4) p-value: <0.001	144.3% (54.3, 234.4), p-value: <0.001
	High (34-56°)	47	-20.7 (-49.6, 25.0)	35	84.9 (14.5, 198.4)	163.1 (81.7, 280.9)		
Wind speed	Low-Med (0-6.2 m/s)	220	REF	57	42.7 (-8.6, 122.8)	47.1 (14.8, 88.6)	-59.6 (-76.6, -30.1) p-value: <0.01	-90.1% (-165.1, -15.1), p-value: <0.05
	High (6.2-10.3 m/s)	79	12.0 (-25.0, 67.2)	25	-35.4 (-59.3, 2.4)	-23.2 (-40.0, -1.7)		

(B) Exposure to PM$_{2.5\text{-}10}$

		Dismantler (n=299)		Burner (n=82)		Burners v. dismantlers within strata of wind	Measure of effect modification on multiplicative scale[a]	Measure of effect modification on additive scale[b]
Effect modifier		N	% change (95% CI)[d]	N	% change (95% CI)	% change (95% CI)	% change (95% CI) of interaction term	RERI (95% CI)[c]
Wind direction variability	Low-Med (0-34°)	252	REF	47	-47.0 (-61.0, -27.9)	-46.6 (-56.1, -35.0)	241.1 (68.0 , 592.5) p-value: <0.01	111.9% (39.6, 184.2), p-value: <0.01
	High (34-56°)	47	-19.8 (-48.4, 24.7)	35	45.1 (-9.61, 133.1)	92.2 (31.3, 181.4)		
Wind speed	Low-Med (0-6.2 m/s)	220	REF	57	13.0 (-26.7, 74.3)	10.6 (-13.4, 41.3)	-55.9 (-74.9, -22.4) p-value: <0.01	-77.4% (-144.4, -10.5), p-value: <0.05

	High (6.2-10.3 m/s)	79	28.6 (-13.1, 89.8)	25	-36.0 (-59.9, 2.2)	-44.0 (-57.8, -25.6)		

Note: All estimates are from linear mixed effect models adjusted for background $PM_{2.5}$, wave of data collection, day of week, temperature and relative humidity. CI, confidence interval, RERI, relative excess risk of interaction.

[a]"Positive" effect modification on the multiplicative scale is defined as an RR > 1 for the interaction term and "negative" effect modification is defined as an RR <1 for the interaction term.
[b]"Super-additive" effect modification on the additive scale is defined as having a relative excess risk of interaction (RERI) >0 and "sub-additive" effect modification is defined as an RERI < 0. CI, confidence interval.
[c] RERI is calculated as RR11 – RR10 – RR01 +1. Confidence intervals and p-values are calculated using the delta method[137];
[d] Percent change calculated by (exp (β) -1)* 100; [e];
[e] "Low-Med" and "High" categories for wind direction variability and wind speed are derived from cut-points at the 75th percentile (34.0 degrees and 6.2 m/s, respectively).

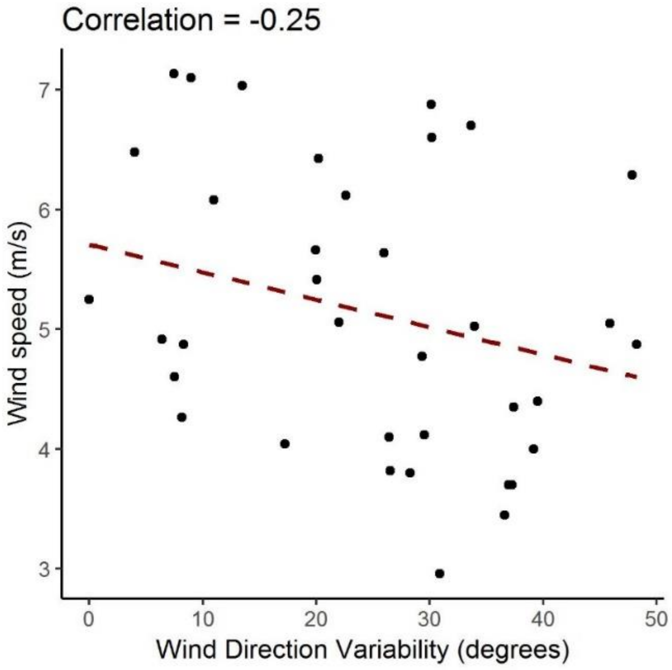
Table 3-4: Opportunities and challenges associated with a hierarchy of air pollution control strategies for reducing emissions from open e-waste burning on an informal e-waste site.

Intervention	Opportunities and challenges
Source elimination	Eliminating the need to engage in burning e-waste would require a method of metal extraction that is equally or more efficient than burning e-waste. An effort made by Pure Earth to reduce emissions from burning wires by providing an automated wire stripping machine highlights the challenges in eliminating burning; despite the new tool, workers at Agbogbloshie continued to burn finely gauged plastic-coated copper wires saying that they were not efficiently processed by the machine[138,139].
Pollution prevention	The replacement of tires and Styrofoam as accelerants could reduce emission toxicity. Alternative technology for burning e-waste (e.g. burn box, incinerator) would reduce byproducts of incomplete combustion and improve process control and metal recovery. Large capital investment, maintenance and technically trained workers are required. New technologies may reduce the number of available jobs.
Pollution control technology	The inclusion of particulate collection methods (e.g. settling chambers, fabric collectors, cyclones) into innovative engineering solutions for burning e-waste that include health and safety in the design could reduce occupational and environmental exposures. Capital investment, maintenance and technically trained workers are needed.
Source relocation and site reorganization of site layout	Geographic separation from receptors (people), stack height increases, reorganization of the worksite layout so that burning e-waste occurs downwind of all other types of work, and restrictions on times during which burning and other activities can be performed may protect nearby populations, but cannot guarantee a reduction in occupational exposures. Relocation would prevent exposure among the estimated 80,000 individuals living adjacent to the Agbogbloshie site[79], in addition to people shopping at the open-air food market and attending nearby primary schools. Prior research found that nearby residents and e-waste workers at Agbogbloshie had comparable risks of PCB exposure, although PCB toxicity among nearby residents could be from other sources (e.g. diet, waste incineration)[40].
Personal protective equipment (PPE)	Provision of basic PPE including boots, gloves and respirators would help reduce injuries and exposure but must be combined with higher order interventions, including proper selection of respirator types, training, fit-testing and PPE maintenance. Long-term capital investment to maintain and replace PPE is essential.
Education and behavioral changes	Education is a prerequisite for any form of intervention. Effective technical interventions and behavioral changes require occupational training and education on the risks associated with e-waste recovery practices. Education can

	further empower workers to advocate for themselves and reduce unnecessary exposures while on the job (e.g., while eating or drinking on site) and in their homes where women and children may be exposed.

3.8 Supplementary Tables and Figures

Supplemental Figure 3-1 Correlation between wind direction variability and wind speed measured during day-time conditions during which sampling took place (between 8AM and 2PM) in Accra, Ghana, 2017-2018.



4 Chapter 4: Cross-Shift Changes in Pulmonary Function and Occupational Exposure to Particulate Matter among E-Waste Workers in Ghana

4.1 Abstract

Objectives: To examine the association between cross-shift changes in pulmonary function (PF) and personal inhalation exposure to particulate matter (PM) among informal electronic-waste (e-waste) recovery workers with substantial occupational exposure to airborne pollutants from burning e-waste.

Methods: Using a cross-shift design, pre- and post-shift PF assessments and concomitant personal inhalation exposure to PM (sizes ≤ 1, ≤ 2.5, and the coarse fraction, 2.5 – 10 µm in aerodynamic diameter) were measured among e-waste workers (n=142) at the Agbogbloshie e-waste site and a comparison population (n=65) in Accra, Ghana. Linear mixed models measured associations between percent changes in PF and personal PM.

Results: Declines in forced expiratory volume in one second (FEV1) and forced vital capacity (FVC) per hour were not significantly associated with increases in PM (all sizes) among either study population despite breathing zone concentrations of PM_1, $PM_{2.5}$, and $PM_{2.5\text{-}10}$ that exceeded health-based guidelines in both populations. E-waste workers who worked "yesterday" did, however, have larger declines in FVC (2.4%, 95%CI: -4.04, -0.81) in comparison to those that did not work "yesterday".

Conclusions: Short-term respiratory-related health effects due to PM exposure among e-waste workers remains unclear. Potential selection bias due to the "healthy worker" effect, the lack of an inception cohort, short shift duration, and inability to measure PF among e-waste workers prior to exposure to the work environment (89% of e-waste workers sleep on site), may explain

the results. Cross-shift studies need to be adapted to informal settings where workers do not "clock-in" at the start of a shift.

4.2 Introduction

Reductions in occupational and environmental health risks associated with the recovery of valuable metals and plastics from used electronic and electrical equipment waste (e-waste) are urgently needed around the globe[14,78]. In informal e-waste recycling sectors common in low- and middle-income (LMIC) countries (e.g., Nigeria, Ghana, Thailand, Argentina), occupational and environmental health and safety regulations are often not enforced, putting workers and nearby communities at risk of exposure to a multitude of physical and chemical pollutants[10,16,74]. Despite a growing body of evidence documenting the occupational and community-level health effects of exposure to e-waste associated pollutants (e.g., lead, chromium, cadmium, flame retardants, dioxins, furans, polycyclic aromatic hydrocarbons (PAHs), particulate matter(PM))[5,20,128], little is known about the respiratory health effects among workers associated with air pollution generated from e-waste recovery practices[23,26,45,46,48,101].

Burning e-waste in open surface fires is a commonly used technique for efficiently eliminating plastic coatings from valuable metals in the informal sector. Measures of PM air pollution from burning e-waste have been shown to exceed extreme concentrations (>500 $\mu g\ m^{-3}$) and be comprised of a high fraction of toxic constituents (e.g. heavy metals, PAHs and flame retardants) posing risks to workers and surrounding communities[16,23,42,43,45–47,102,109]. Other techniques used to process e-waste, such as manual dismantling of generators, cathode ray tubes, and fluorescent lighting, for example, present additional inhalation hazards including metal contaminated dust and vapors[108].

A large body of epidemiologic evidence links short- and long-term exposure to PM ($\leq$ 10 µm and $\leq$ 2.5 µm in aerodynamic diameter) with pulmonary, cardiovascular and in some cases cerebrovascular morbidity and mortality[54,57,62,69]. Moreover, measured associations between PM concentrations and health effects exhibit a dose-dependent relationship with no known threshold below which no adverse effects occur[55,59]. E-waste workers exposed to high concentrations of PM and co-occurring inhalation hazards (e.g., carbon monoxide (CO), PAHs, metals) are likely to exhibit accelerated declines in pulmonary function. The severity of declines may differ by specific work activities.

The cross-shift study design has been used in formal occupational settings to establish robust epidemiologic evidence on the associations between acute inhalation hazards (those experienced across the work-shift or week) and respiratory health[140,141]. Cross-shift studies enable each study participant to serve as their own referent, reducing the impact of confounding, and do not require a long-term follow up. The lack of appropriate reference populations and establishing a long-term follow-up are two of the many challenges limiting existing epidemiologic data among informal e-waste workers.

Few occupational studies have measured acute responses to PM, as it is not a regulated chemical exposure. Using data from wildland firefighters, Gaughan et al. (2014) found a cross-shift decline in pulmonary function (forced expiratory volume in one second (FEV1)) associated with increased exposure to levoglucosan, a byproduct of biomass burning measured in PM (<10µm)[142]. Similarly, among firefighters responding to a controlled burn, Slaughter et al. (2004) found a measured decline in pre- and post-shift FEV1; however the decline was not significantly associated with concomitant exposure to PM (<3.5µm)[143]. And in non-occupational settings, emerging evidence establishes an association between acute respiratory effects, including pulmonary function declines and reduced exercise performance, and short-term exposure to diesel exhaust and PM ($\leq$ 1 and $\leq$2.5 µm in aerodynamic diameter) in healthy individuals and in those with asthma, chronic obstructive pulmonary disease, and ischemic heart disease[144–149].

Using data collected at the Agbogbloshie informal e-waste recovery site and a reference community in Accra, Ghana, this study evaluates whether acute changes in pulmonary function are associated with occupational exposures to personal PM from e-waste recovery activities using a highly sensitive cross-shift study design. The first aim is to evaluate the association between cross-shift changes in pulmonary function and personal exposures to PM_1 (<1 µm), $PM_{2.5}$ (<2.5 µm), coarse fraction PM (2.5 µm -10 µm), and self-reported pre-shift exposures among e-waste recovery workers and a reference population. The second aim is, among e-waste workers only, to evaluate the association between cross-shift changes in pulmonary function and activities performed during the work shift. The results will contribute to the limited epidemiologic evidence on acute respiratory health effects associated with unusually high personal PM concentrations among e-waste workers in Accra, Ghana.

4.3 Methods

4.3.1 Study Sample

Study participants were enrolled in the West Africa-Michigan CHARTER II for GeoHealth (GeoHealth) (N=207), a longitudinal cohort study with four waves of data collection designed to assess environmental and occupational health among e-waste recovery workers at the Agbogbloshie e-waste site in Accra, Ghana. Eligible participants (N=131) included male e-waste recovery workers from the Agbogbloshie e-waste site (n=81) and male residents from a reference population (n=50) living in the Madina Zongo (MZ) district of Accra (Figure 1) who completed personal shift sampling during the second (August 2017 – October 2017) and/or the third wave (January-April 2018) of data collection.

Details on the geographic setting and participant recruitment at Agbogbloshie have been described previously[42,109]. An attempt to enroll an inception cohort of e-waste workers at Agbogbloshie was unsuccessful, as information on when or if a new worker arrived to the site was unavailable. In the study, the role of the reference population is to provide otherwise unavailable background levels of personal PM inhalation exposure and respiratory health of Accra residents with similar socio-, cultural- and economic characteristics of e-waste workers. The MZ community members were selected as an appropriate reference population based on their geographic separation from e-waste associated pollutants and similar religion and region of origin to the e-waste worker population. MZ is comprised of housing structures and small-scale businesses providing community needs and is surrounded by a high traffic four-lane road (N4). A sufficient number of individuals in both study locations volunteered to participate. Compensation at each wave included 30 Ghana Cedis (approximately 7 USD), lunch and a t-shirt. Informed consent was obtained and all study questionnaires were administered by trained, local interpreters in the preferred language of the participant. Institutional Review Board approval was obtained from the University of Ghana and the University of Michigan.

4.3.2 Data Collection

4.3.2.1 Baseline health Interviews

A baseline health survey was completed for each participant at their initial study visit (wave I or wave II). The survey included questions on socio-demographics, tobacco use and indoor cooking habits adapted from the Ghana Demographic Health Survey[150]. Standard respiratory symptoms (see Table 1) were derived from the Medical Research Council questionnaire (MRCQ) on respiratory symptoms[151]. Symptoms included: (1) Usual cough (answered yes to “do you usually cough first thing in the morning?” or “do you usually cough during the rest of the day or at night?”); (2) Usual phlegm production (answered yes to “do you usually bring up any phlegm from your chest during the day or at night?”); (3) Phlegm production longer than three months (answered yes to “do you bring up phlegm like this on most days/nights for as much as three or more months in each of the last two years?”); (4) Chronic bronchitis (defined as cough longer than three months and phlegm production longer than three months); (5) Breathlessness when walking (answered yes to “do you get short of breath when walking with other people of your own age on level ground?”); (6) Severe breathlessness when walking (answered yes to “do you have to stop for breath when walking at your own pace on level ground?”); (7) Wheezing (answered yes to “have you had wheezing or whistling when you did not have a cold or flu?”); (8) Chest tightness (answered yes to “have you been woken up with a feeling of tightness in your chest at any time in the last 12 months?”); And , (9) shortness of breath (answered yes to “have you had an attack of shortness of breath that came on during the daytime when you were at rest at any time in the last 12 months?” or “have you been woken by an attack of shortness of breath at any time in the last 12 months?”).

4.3.2.2 Personal inhalation exposure to Particulate Matter

Personal inhalation exposure to size-specific PM was estimated using measurements from a 5-channel optical particle counter (Aerocet 831, Met One Instruments, Oregon, USA) worn in a sampling backpack by each participant during a partial work-shift. Specific details on the sampling protocol and how the device works have been described previously[109]. The device logs continuous measures (1 every minute) of particle counts (sizes ≤ 1, ≤ 2.5, ≤ 4, and ≤ 10 µm in aerodynamic diameter) from the participant's breathing zone and converts them into size-specific mass measurements (as µg m^{-3}). Measures of PM_{10} exceeding 2000 µg m^{-3} (0.3% of the data, n=369 minutes) were censored to avoid potential bias from coincidence error (i.e., when multiple small particles appear as one larger particle resulting in an overestimate of large-channel particles). $PM_{2.5-10}$ was derived by subtracting the fraction of PM $\leq$ 2.5 from PM $\leq$ 10 µm. Shift averages for PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ were derived for each participant. Shift peak concentrations were defined as the maximum 5-min means for PM_1, $PM_{2.5}$ or $PM_{2.5-10}$ concentrations for each participant.

Deployment of the personal sampling backpacks for both study groups occurred between 8AM and 11AM and retrieval occurred between 12PM and 3PM. Participants were initially asked to wear the sampling backpacks for a minimum of 6 hours. The sampling time was initially reduced to 4 hours during wave 2, in order to minimize inclusion of non-work activities among e-waste workers, which were observed to increase in the latter part of the shift. A subsequent reduction in sampling duration from 4 to 2 hours occurred during Harmattan season (wave 3), when winds off the Saharan dessert that transport sand and dust across the region between November and February were preventing equipment in the sampling backpacks from functioning.

4.3.2.3 E-waste recovery activities

Image-derived time-activity data were generated for a sub-cohort of e-waste worker participants (n=50) during their work-shifts. Time-lapse images (1 per minute) were taken using a wide-angle GoPro Hero4© camera that was mounted to the shoulder strap of the personal sampling backpack. Details on how the images were processed to derive time-activity data have been described previously[109]. Activity categories included: burning e-waste, dismantling e-waste, sorting/loading e-waste, buying/selling e-waste, transporting e-waste and scrap materials, other e-waste activities, other work activities unrelated to e-waste recovery, use of a motorcycle or car, walking, bicycling, smoking or in the presence of tobacco smoke, and not actively working (i.e. sitting, eating or drinking, cell phone use, prayer, and communicating with others).

4.3.2.4 Pre-and Post-shift interviews and self-reported pre-shift exposures

Pre-shift and post-shift interviews were performed for each participant prior to the deployment of the personal sampling backpack (between 8AM and 11AM) and after backpack retrieval (between 12PM and 3PM). The pre-shift survey included questions on current respiratory symptoms and pre-shift exposures. Current respiratory symptoms included: “irritation of burning of the eyes nose, or throat?”; “cough?”; “wheezing or whistling sound in your chest apart from colds?”; “shortness of breath, difficulty catching your breath, or a smothering feeling?”; and “chest tightness or a sensation of a band around the chest?”. Pre-shift exposures include working “yesterday” (the day before the pulmonary function test) and working prior to the pre-shift pulmonary function test (same day). The post-shift survey included the same questions on current respiratory symptoms and tobacco use during the shift. Incident respiratory symptoms were defined as those reported on the post-shift questionnaire and not on the pre-shift questionnaire.

4.3.2.5 Cross-shift Pulmonary Function

Pre-shift and post-shift pulmonary function tests were performed at the same time as the pre- and post-shift interviews; prior to the deployment of the personal sampling backpack (between 8AM and 11AM) and after backpack retrieval (between 12PM and 3PM). Pulmonary function was assessed using the handheld EasyOne Diagnositic spirometry device (NDD Medical Technologies, Andover, MA) following the guidelines of the American Thoracic Society (ATS)[152]. Two examiners, a local physician and emergency medical technician, were trained on how to use the device and administer the test. Before beginning the test, age, height and weight were recorded and the maneuver was demonstrated. Participants were coached to take a maximal inspiration and then blast the air out of their lungs into the device as hard, fast and as long (minimum 6 seconds) as they could. Participants performed a maximum of six maneuvers, and were asked to stop after performing three maneuvers that were considered adequate by both the examiner and an automated quality grade. The device stored the best three maneuvers for each participant.

Pulmonary function parameters of interest included cross-shift changes in forced vital capacity (FVC), forced expiratory volume in one second (FEV1) and the FEV1/FVC ratio. Before calculating cross-shift measures, two trained reviewers graded the acceptability of each of these parameters for each maneuver following the acceptability criteria of the ATS[153]. The duration of the exhalation had to be $\geq$ 4 seconds with a plateau on the volume-time curve showing no change in volume for at least 1 second. A third reviewer was consulted in the event of a discrepancy. As per ATS criteria, the best FEV1 and best FVC values were used even if from two different maneuvers and, when possible, the FEV1/FVC ratio was calculated from the curve with the largest sum FEV1 plus FVC. FEV1 and FVC values were graded for between-maneuver repeatability criteria, i.e.,a difference $\leq$ 0.15 L between the two largest of each values. However repeatability was not a basis for exclusion as this has been shown in prior research to produce selection bias[154]. "Valid" measures are those that met acceptability criteria, and "reproducible" measures are valid measures that also met repeatability criteria. Cross-shift change in FEV1, FVC and FEV1/FVC ratio were calculated for all participants with valid paired pre- and post-shift FEV1, FVC or FEV1/FVC ratio measures. A cross-shift change is defined as the percent change in FEV1, FVC and FEV1/FVC ratio per hour and calculated as: [(post-shift value – pre shift value) / pre-shift value * 100] / shift length (hours)].

Valid test results were expressed as the percentage of the predicted values expected for a "normal" population of the same sex, age, height and race using equations derived from a population-based study of 7,429 asymptomatic, non-smoking participants of the NHANES-III survey[155]. While there are no established predicted values for the African continent or Ghanaians in particular[156], African-Americans are expected to share substantial common ancestry. Among the NHANES-III sample used to create the predicted values, there are a total of 2,508 African-American participants[155].

4.3.3 Statistical Methods

Study groups (e-waste and reference population) were compared across socio-demographic characteristics, baseline respiratory health status, baseline pulmonary function (absolute values and percent predicted), personal inhalational exposure to PM_1, $PM_{2.5}$, $PM_{2.5-10}$, pre-shift exposures and incident respiratory symptoms. The primary health outcomes included cross-shift changes in pulmonary function measures (FEV1, FVC, and FEV1/FVC ratio). The distributions of PM measures were log-normal. A binary log transformation was used; a one-unit change in PM represented a two-fold or doubling effect of PM exposure on the outcome. Associations between cross-shift changes and exposures were estimated using linear mixed effects (LME) models. LME models include a random intercept for participant to account for correlated outcomes among participants in more than one wave of the study. In cases when the random effect for subject was approximately zero, linear regression was used to avoid overfitting the model. The main effects for study group, PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ (shift mean and peak concentrations), and pre-shift exposures are presented for each of the primary health outcomes. All models were adjusted for *a priori* confounders including age, height, the use of cigarettes during the shift, study wave, and day of week. Participants with a history of asthma (n=2) were excluded from the regression analyses. No participants reported a history of tuberculosis. Differences in the effects of personal PM and pre-shift exposures on cross-shift change in pulmonary function between study groups were tested using both interaction terms added to the fully adjusted models and stratified models. Among e-waste workers only, linear regression models adjusted for age, height and smoking cigarettes during the shift were used to estimate the associations between activities performed during the shift and cross-shift changes in pulmonary function. Activity was parameterized as both a binary variable (performed the activity or not) and a count variable (number of minutes spent performing the activity). All analyses were accomplished using the statistical software R[80].

4.4 Results

4.4.1 Sample

Personal sampling was conducted during 175 monitored shifts (from 131 unique participants; 81 e-waste workers and 50 members of the reference population). Complete data sets (including personal PM and a valid cross-shift FEV1 and/or FVC) were available for 156 shifts (120 unique participants; 73 E-waste workers and 47 members of the reference population). More e-waste worker participants (9%) than reference population participants (6%) were removed from the analysis due to the lack of a cross-shift pulmonary function measures that met ATS acceptability criteria. Socio-demographic characteristics of participants with complete data did not differ significantly from the full cohort (data not shown).

The population of MZ residents chosen as the reference population for this study differed from the e-waste worker population across the majority of socio-demographic characteristics (Table 1). In comparison to the reference population, e -waste workers were younger, with lower incomes and education, had a higher prevalence of current cigarette smokers (25% versus 6%) and lived less frequently in an abode where indoor cooking routinely took place (16% versus 51%). Among the reference population that did cook indoors, liquid petroleum (23.9%) or electric stoves (10.9%) were most common followed by (non-electric) stove or coal pots with (8.7%) and without vents (4.3%). The majority of both populations were Muslim in a majority Christian city and country. Among the 70% of those currently employed in the reference population, "current" jobs included traders (n=15), skilled workers (e.g., tailors, electricians) (=14), *tro-tro* (public van) drivers and driver assistants (n=7) and other (n=9).

4.4.2 Baseline respiratory health status

There were no self-reported cases of tuberculosis and only two cases of asthma confirmed by a doctor among the sub-cohort (Table 2). E-waste workers reported a higher prevalence of all of the 10 respiratory symptoms queried in comparison to the reference population; the only differences in symptom prevalence with p-value's below 0.10 were wheezing (23.6% versus 8.5%, p-value: 0.049 and chest tightness (32.9% versus 17.0%, p-value: 0.089).

4.4.3 Exposures to particulate matter

The average duration of monitored shifts was longer for the reference population (265.9, range 171 - 399 min) than the e-waste workers (230.3, range: 148 - 370); 18% of e-waste workers had a shift length $\leq$ 3 hours in comparison to 3% of the reference population (see Figure 2). Mean and peak personal PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ concentrations were calculated for each participant's shift and are summarized by study group in Table 4-3. Mean and peak personal PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ concentrations were significantly higher (p-value < 0.001) among the e-waste workers in comparison to the reference population, (Table 4-3). Prevalence of tobacco use during the work shift was higher among e-waste workers than the reference population

(86% versus 14%, p-value: <0.001). A significantly larger proportion of e-waste workers in comparison to the reference population reported working the day before (69% versus 31%, p-value <0.001) and working prior to the pre-shift pulmonary function test (74% versus 26%, p-value <0.001) (Table 3). Less than half of the reference participants (39%) reported working *during* the shift; among those that did, work activities associated with the highest tertiles of PM_1, $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations included selling marijuana, “trading”, “digging” and “tiling”.

4.4.4 Cross-shift change in pulmonary function

Among the 156 monitored shifts with complete data, a total of 153, 123 and 120 cross-shift measures of FEV1, FVC and FEV1/FVC ratio were derived. Of the 156 eligible sessions, 46% (n=72) were reproducible according to between-maneuver repeatability criteria (i.e.,a difference $\leq$ 0.15 L between the two largest of each values) [157] (supplemental Table 1). The proportion of reproducible pulmonary function maneuvers among e-waste (56%) and reference population (54%) participants were similar.

Pre-shift (baseline) pulmonary function measures for the total cohort and by study group are described in Table 4-4. Average pre-shift FEV1 and FVC measures for the whole cohort were 86% and 90% of the predicted value for a normal population of the same age, height and race, respectively (Table 4-4). When comparing study groups, pre-shift FEV1 and FEV1/FVC ratio were lower among e-waste workers (Table 4). Pre-shift FVC averages and percent predicted values were modestly higher among e-waste workers in comparison to the reference population. These results were replicated when using only reproducible values (Supplemental Table 1).

Unadjusted cross-shift changes in FEV1 and FVC were negative for both study groups indicating a decrease in pulmonary function throughout the work-shift (Table 4). Pre- and post-shift FEV1/FVC ratios did not differ for either study group. Post-shift FEV1 values were significantly lower than pre-shift FEV1 values for e-waste workers and the reference population (p-value=0.007 and 0.043). Differences in pre- and post-shift FVC and the FEV1/FVC ratio did not reach statistical significance for either study group. E-waste workers had larger cross-shift changes in FEV1 ($-2.2\pm9.4\%$) and FVC ($-1.2\pm7.1\%$) than the reference population ($-1.5\pm6.4\%$ and $-0.8\pm6.0\%$ respectively); however the differences did not reach statistical significance. More e-waste workers (18.7%) than the reference population (7.8%) had a post-shift FEV1 percent predicted below 70% (p-value: 0.094). When using only reproducible results, the reference population instead of the e-waste workers had greater decreases in both FEV1 and FVC. However, the differences between groups did not reach statistical significance (Supplemental Table 1). Essentially no change in the FEV1/FVC ratio for either study group was observed when using only reproducible results.

4.4.5 Association between PM and cross-shift change in pulmonary function

Measures of association between personal inhalation exposure to PM_1, $PM_{2.5}$ or $PM_{2.5\text{-}10}$ and percent change per hour in FEV1, FVC, and FEV1/FVC ratio were expected to be negative, indicating a decrease in pulmonary function throughout the shift with increasing levels of PM concentration. Results for the full sample and stratified by study group are summarized in Figure 3 and Supplemental Table 4-2. As a whole, the results show no signal that increasing levels of PM were associated with a decrement in pulmonary function throughout the work-shift in this sample. Contrary to our expectations, the directions of the estimated risk ratios were overwhelmingly positive; however, regardless of the direction, the 95% confidence intervals for all tested associations crossed zero, indicating no effect of PM on pulmonary function. Moreover, study group was not associated with cross-shift changes in pulmonary function; e-waste worker participants in comparison to the reference population had a 0.06 (95%CI: -0.88 to 1.01), 0.04 (95%CI: -0.84 to 0.91) and -0.12 (95%CI: -0.75 to 0.51) percent change in FEV1, FVC and FEV1/FVC ratio per hour, respectively (Figure 3, Supplemental Table 2).

Measures of association between study group, PM and cross-shift change in FEV1 (n=65) and FVC (n=35) using only reproducible pulmonary function values are summarized in supplemental Figure 1. No associations between study group and percent changes in FEV1 or FVC were observed after adjusting for age, height and smoking during the shift (Supplemental Figure 1). A doubling of mean and peak PM_1 concentrations throughout the work-shift, however, was associated with 0.81 (95%CI: 0.17, 1.44) and 0.53 (95%CI: 0.06, 1.00) percent increases in cross-shift FVC. Similarly, positive associations between $PM_{2.5}$ (mean and peak) and cross-shift FEV1 were found; however the 95% confidence intervals all crossed zero.

4.4.6 Association between pre-shift exposures and cross-shift change in pulmonary function

Self-reported exposures experienced prior to the pre-shift sampling period, including working “yesterday” (the day before the pulmonary function test) and working prior to the pre-shift pulmonary function test (same day), are expected to reduce any observed decrement in pulmonary function by causing pre-shift pulmonary function measures to be lower than what would be expected had those exposures not occurred. In our sample, working prior to the pre-shift pulmonary function test was not associated with a measured increase or decrease in FEV1, FVC or the ratio. Working “yesterday”, however, was unexpectedly associated with a 1.22% decrease in FVC per hour (95%CI: -2.18, -0.27) (Supplemental Table 2). When stratified by study group, e-waste worker participants who reported working “yesterday” had an average 2.4% (95%CI: -4.04, -0.81) and 1.2% (95%CI: -3.07, 0.69) cross-shift decrement in FVC and FEV1, respectively, while essentially no association was observed among the reference population (Figure 4-4, Table 4-3). When using only reproducible values, the same trend was observed (Supplemental Figure 2).

We conducted a sensitivity analysis that examined the association between working “yesterday” and pre- and post-shift percent-predicted values of FEV1 and FVC, in order to better understand how previous exposures were affecting pulmonary function,. Among e-waste workers only, working “yesterday” was associated with a 9.2% (95% CI: -18.49, -0.09) and a 12.07% (95% CI: -21.36, -2.78) lower pre-shift FEV1 and post-shift FEV1 predicted value, respectively, in comparison to e-waste workers that did not work “yesterday” (See Supplemental Table 4-3). These results signify that e-waste workers who worked “yesterday” not only started the day with a lower baseline FEV1 than those that did not work “yesterday”, but they ended the shift with an even lower one. Working “yesterday” was not associated with pre-shift FVC predicted values among e-waste workers (RR: 0.68, 95% CI=-9.49 to 10.85). However, it was associated with a 6.49% lower post-shift FVC predicted value (95%CI= -17.37, 4.38); this result signifies that working “yesterday” was associated with a steeper decline in FVC throughout the day, but that working yesterday did not influence their pre-shift FVC (Table 5). Among the reference population, working “yesterday” was positively associated with pre- and post-shift

FEV1 and FVC predicted values; however, none of the associations reached statistical significance.

4.4.7 Incident Symptoms and pulmonary function

E-waste workers had a higher incidence of all symptoms in comparison to the reference population (Supplemental Table 4-4). More than twice as many e-waste workers than reference population reported incident chest tightness (9.8% v. 3.1%) cough (17.4% v. 11.1%), shortness of breath (9.8% v. 6.2%) and wheezing (16.3% v. 7.8%). However, the total numbers were small and the difference did not reach statistical significance at the 0.05 alpha level. No statistical associations were observed between incident symptoms and cross-shift changes in pulmonary function (data not shown).

4.4.8 Activities performed by e-waste workers and pulmonary function

The average length and range of time for each activity performed by the e-waste worker participants with image-derived data (n=50) is summarized in Table 4-5. The most common activities performed among the e-waste workers included not actively working (e.g., sitting, cell phone use, communicating), walking, motorcycle or car use, sorting/ loading and dismantling e-waste. Very few participants (n=5) performed burning e-waste during the monitored work shift.

Among the activities performed by five or more participants, comparisons between unadjusted cross-shift changes in FEV1, FVC and FEV1/FVC ratio for those who performed the activity to those who did not showed no measurable differences (data not shown). In models adjusted for age, height and smoking during the shift, associations between all of the activities and percent changes in FEV1, FVC or FEV1/FVC were all close to zero (Figure 4-5). A modestly protective effect of burning e-waste and dismantling e-waste was found; workers who burned and dismantled e-waste at least once during the work-shift had a 0.38 (-1.84, 2.59) and a 0.69 (-1.11, 2.50) percent increase in FEV1 per hour, respectively, in comparison to those who did not perform those activities at all. Interestingly, not actively working was associated with a -1.05 (-2.88, 0.78) percent decrease in FEV1 per hour in comparison to those who did not perform that activity (i.e., were not ever 'not actively working') at all. When activity was parameterized as a count variable (length of time performing the activity), similar results were found with one exception; an increase in the amount of minutes a worker performed dismantling was associated with an improvement in FVC per hour ((Supplemental Figure 3).

4.5 Discussion

The aim of this study was to examine the effect of personal inhalation exposure to PM on pulmonary function among e-waste recovery workers and a reference population in Accra, Ghana. A cross-shift study design that combined pre- and post-shift pulmonary function assessments with personal monitoring of PM exposure was used. Personal inhalation exposure to PM_1, $PM_{2.5}$ and $PM_{2.5\text{-}10}$ among e-waste workers at the Agbogbloshie e-waste site were nearly double the concentration levels experienced by the comparison group, Accra residents who live and work near a heavily trafficked road. Both populations, however, experienced mean concentrations of personal $PM_{2.5}$ that exceeded the WHO's ambient Air Quality Guideline (24-hour mean: 25 $\mu g\ m^{-3}$) and for e-waste workers specifically, the Interim target-2 (IT-2) (24-hour mean: 50 $\mu g\ m^{-3}$)[56]. Following an average monitored shift of 4 hours (± 44 min), declines in pulmonary function (FEV1 and FVC) were observed among e-waste workers and the reference population. Although declines in FEV1 and FVC were largest among e-waste workers, they were not significantly different from the reference population. Exposure to concomitant personal PM_1, $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations was not associated with cross-shift declines in pulmonary function in either study group. Cross-shift changes in pulmonary function were also not significantly associated with e-waste recovery activities performed during the shift. Lessons learned during this initial effort to measure a highly sensitive pulmonary function outcome among informal e-waste workers can inform future studies in other non-traditional occupational settings that are grappling with similar challenges (e.g. the lack of separation between work and life activities).

It is possible that e-waste workers did not experience a cross-shift decrement in pulmonary function due to high concentrations of PM exposure on the work site. The findings may be attributable to the "healthy worker" effect; current workers selected for the study may still be able to tolerate high levels of PM exposure and be more resistant to short-term respiratory effects than the workers who have left the job due to health complications[77]. E-waste recovery workers at Agbogbloshie have reported in interviews that workers leave the site and return to their family homes in Ghana's Northern region when health complications arise[50]. Health-related job selection has been attributed to similar findings among coal miners in which occupational exposure to respirable dust was not associated with declines in pulmonary function among current workers,[158] and attenuated among current miners in comparison to former miners[159–161]. The modestly improved cross-shift changes in FEV1 and FVC values among workers who performed burning and dismantling supports this hypothesis; i.e., that workers performing burning and dismantling can still handle the high exposures associated with these activities[109].

E-waste workers may have experienced a decline in pulmonary function associated with e-waste-related exposures only during their initial months of employment. Prior studies have observed differential effects of metal working fluids and respirable dust among machinists and coal miners, respectively, according to years of employment; the dose-response curve flattens out with increasing years of employment suggesting a threshold effect[158,162,163]. In our sample, the average length of employment at Agbogbloshie among e-waste participants (8.8 $\underline{+}$ 6.6 years) was too long to measure initial reductions in pulmonary function. Among the participants who worked less than 1 year on the site (n=8), pre-shift FEV1 percent predicted values were approximately 5% lower than those who worked longer than 1 year, however no significant differences in cross-shift changes in FEV1 or FVC were observed.

In addition to long durations of exposure, e-waste workers were uniformly exposed to breathing zone PM concentrations well above health-based standards. Understanding the dose-response curve for workers and healthy populations following long-term exposures to elevated concentrations of PM requires further investigation. There is limited research examining respiratory health outcomes among workers with chronic and elevated PM exposure. Among traffic policeman in China exposed to elevated shift concentrations of personal $PM_{2.5}$ (mean: 115.40±46.25 µg m^{-3}), Zhao et al. (2015) found increasing levels of $PM_{2.5}$ associated with increased inflammatory markers and reductions in FEV1 and FEV1/FVC ratio[164]. At the same time, in a study among truck drivers in China, also exposed to elevated shift concentrations of personal $PM_{2.5}$ (127 ± 69 µg m^{-3}), no association between pulmonary function and mass concentrations of PM2.5 were observed[165]. Baccarelli et al. (2014) did, however, find inverse associations between elemental components of personal $PM_{2.5}$ (including silicon, aluminum, calcium and titanium) and pulmonary function (FEV1 and FVC) highlighting the importance of examining associations between respiratory health and PM consituents (e.g., elemental components and organic compounds), in addition to the mass concentration[165].

Alternatively, e-waste workers may have experienced a cross-shift decrement in pulmonary function, but it was masked by artifacts of the study design. Throughout the study, we learned that pre-shift pulmonary function tests were not measured before participants were exposed to, possibly substantial, PM concentrations from the work-site, cooking, and/or road traffic; a large majority of e-waste workers reported living at the e-waste site (89%) and having already worked prior to the pre-shift test (74%). Among the reference population, approximately 20% reported having been exposed to dust or smoke from road-traffic and cooking food prior to the pre-shift assessment. Smoke from indoor cook-stoves and traffic-related PM exposure are independent risk factors of pulmonary function decline[64,144,145].

In addition to the lack of a true "pre-shift" pulmonary function assessment, any cross-shift changes may have been diluted by the diurnal variation in pulmonary function. A limitation of using pulmonary function measures without a resting control is that we do not know how much of the variation is due to natural diurnal variation. Prior research on the circadian variation in pulmonary function show that FEV1 and FVC typically peak around noon and then start a slow descent which continues throughout the rest of the day for FEV1 and has a second smaller rise in the late afternoon, early evening hours for FVC[166]. Given the lack of a true pre-shift pulmonary function assessment and the diurnal variation in pulmonary function, a shift duration of 4 hours (± 44 min) from morning to mid-afternoon may have been too short to capture a measurable change in lung function due to occupational exposures.

The unadjusted cross-shift changes in FEV1 and FVC among e-waste workers provide some evidence of possible respiratory health effects due to e-waste associated pollutants. E-waste workers had a greater decrease in FEV1 in relation to FVC; a pattern indicative of obstructive lung diseases[167]. The primary biological mechanisms underlying respiratory health effects due to

PM are inflammation and oxidative stress[53,64]. PM and its constituents (e.g. black carbon, metals and PAHs) can penetrate and irritate different areas of the lung's mucous membrane, often leading to obstructed airways[53]. The common use of tobacco products among the e-waste worker participants (25%), however, cannot be ruled out as a cause of observed declines in lung function.

Respiratory effects in this population may occur over the course of multiple days instead of a partial work-shift as measured in this study. The steeper decline in pulmonary function among e-waste workers who reported working the day before the cross-shift pulmonary function assessments, in comparison to those who did not, provides some evidence of respiratory health effects from e-waste associated PM pollution occurring in the range of 24-96 hours before the measurements took place. Time-series studies using distributed lag models to examine the association between ambient air pollution and health outcomes, such as mortality, asthma and hospitalizations for myocardial infarction, have found larger effect sizes for 1 to 6 day lag exposures in comparison to same-day exposure[168–171]. Future studies in informal settings where workers commonly live and work in the same vicinity should aim to monitor participants for a longer period, possibly over the course of multiple, consecutive work days starting with the lightest exposure day. With participant cooperation, performing spirometry at multiple time-intervals could help distinguish between diurnal variation and exposure-related change in pulmonary function.

The high incidence of respiratory symptoms, particularly cough (17%) and wheeze (16%), reported by e-waste workers following an average of 4 hours of work is notable. In research among World Trade Center responders exposed to toxic dust from the collapse of the World Trade Center in 2001, the frequency and severity of respiratory symptoms were found to be associated with small airways abnormalities that were initially undetected through the use of spirometry[172,173]. Forced oscillation techniques to assess distal lung function were recommended as a screening tool to detect small airway disease and COPD onset[174]. In other words, the use of routine spirometry may not have been sensitive enough to detect abnormalities in lung function among symptomatic e-waste workers.

Given the high variability in pulmonary function outcomes, spirometry, as performed in this study, may have had low levels of accuracy. The standard deviations in valid cross-shift FEV1 and FVC response variables for the whole cohort, ±8.25 and ±6.67, respectively, were high. In a sensitivity analysis, we compared the residual variance for cross-shift FEV1 and FVC response variables between study groups using a distributional model adjusted for age, height and the use of cigarette smoking during the shift ("brms" package). We found that the residual variance was significantly higher for FEV1 (95% CI: 2.33, 3.14) and FVC (95% CI: 1.88, 2.60) among the e-waste study group in comparison to the reference population. Unequal variance may be a result of field conditions, unmeasured factors that we do not understand or challenges in eliciting a valid pulmonary function test among e-waste workers. There is some evidence that repeated pulmonary function maneuvers exacerbate airflow narrowing among individuals with prevalent obstructive lung diseases, including asthma, making it harder to achieve valid test results[175]. When using only reproducible pulmonary function values, the main results did not change; however the reproducible models had limited power and may be excluding participants with accelerated declines in pulmonary function rather than those with measurement error[154] .

The sample of MZ community members was not comparable with the e-waste workers with respect to age, education, income, the use of indoor cooking or smoking status. Therefore, comparisons between the e-waste worker and reference community participants had limited value beyond highlighting challenges associated with finding populations comparable with informal workers. However, the data collected among the MZ participants offered insight into respiratory health and background levels of personal PM among Accra residents; 39% of the reference participants reported working during the shift, suggesting that average and peak levels of personal $PM_{2.5}$ exposure in or near personal households were close to 35.6 and 106.6 µg m^{-3}, respectively. Known sources of PM pollution for the reference community include indoor cooking and traffic-related air pollution. The highest observed occupational sources of PM exposure were among participants trading goods (most likely at the congested MZ junction), selling marijuana, and construction (i.e. "digging" and "tiling"). We also expect high personal PM exposures among *tro-tro* drivers and the driver assistants; only one of the participants who reported working on a *tro-tro* worked on the day of sampling and his mean $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations were 36.9 and 41.9 µg m^{-3}, respectively.

4.5.1 Strengths and limitations

The application of a gold standard, cross-shift study design in an informal occupational setting is a strength of this study. The combination of a highly sensitive diagnostic tool to assess pre- and post-shift pulmonary function with continuous measures of personal inhalation exposure to PM (size <1, <2.5 and $_{2.5\text{-}10}$) provided a rich dataset from which causal evidence can be generated, in addition to contributing to the limited available evidence on respiratory health among residents of Accra, Ghana. Continuous PM concentrations allowed us to examine the effects of both daily mean and the very high peak PM concentrations which are unique to e-waste recovery, on pulmonary function. The use of image-derived time activity data provided the opportunity to examine whether activities may encapsulate respiratory hazards that may or may not be captured by PM measures (e.g. location, physical exertion, co-polluting gases).

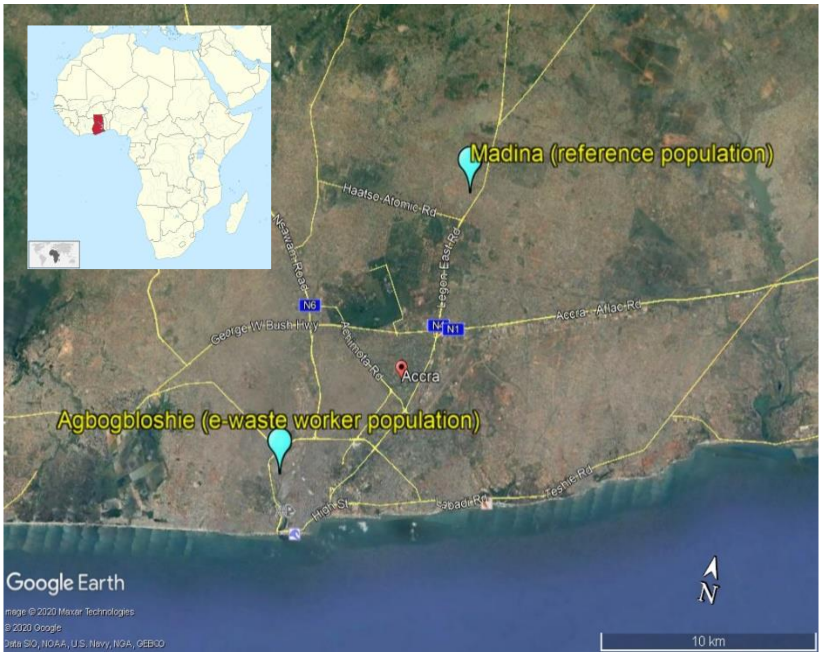
This work has several limitations. Breathing zone concentrations of PM were estimated using optical measurements rather than gravimetric mass measurements (considered the reference approach), which may be associated with measurement error. Based on simulations and experiments described in our previous work, it was concluded that the optical-based measurements underestimated the true PM concentrations and that particle losses were greatest among the larger sized particles (i.e. $PM_{2.5\text{-}10}$)[42,136]. Pre-shift pulmonary function assessments were performed after the majority of e-waste worker participants started their workdays. In fact, most workers sleep at the e-waste site, making it nearly impossible to perform a true baseline pulmonary function assessment. The shift duration may have been too short to capture significant changes in pulmonary function considering the lack of a true "pre-shift" assessment. Limited statistical power, particularly among the reference population, impeded our ability to make comparisons that we would have liked to make (i.e. between e-waste workers who did not work yesterday *and* did not work prior to the pre-shift assessment with the same subcategories among the reference population). The absence of an inception cohort limited our ability to observe possible early decrements in lung function experienced among new workers in comparison to seasoned workers. Creative solutions to gathering information on when workers first arrived at the site are needed. At Agobgbloshie, this information was not readily available. The high degree of variability in the pulmonary function data may be indicative of inaccuracies; such uncertainty in the data is hard to overcome. The sample size of e-waste worker participants with image-derived activity data was too small to establish reliable results. The reference community was not comparable to the e-waste worker participants with respect to most socio-demographic variables, use of indoor cooking and smoking habits, which limited our ability to make strong statistical comparisons. Image-derived time-activity data for the reference population was not generated, but could, in the future, help identify specific behavioral or occupational risk factors of acute respiratory health effects among the MZ residential community.

4.5.2 Conclusions and recommendations

E-waste recovery is associated with high concentrations of PM pollution[45,105,109]. The short- and long-term respiratory-related occupational health burden due to e-waste associated PM pollution is not yet known, but likely to be substantial. In using a cross-shift study design that combined morning and afternoon pulmonary function assessments with personal monitoring of PM pollution, we contributed to a limited knowledge base on acute respiratory health effects from e-waste recovery work. In this sample, cross-shift declines in pulmonary function were not associated with concomitant PM_1, $PM_{2.5}$ and $PM_{2.5\text{-}10}$ breathing zone concentrations. The limitations we encountered in conducting the study, including the inability to capture a true pre-shift pulmonary function assessment among e-waste workers who sleep at the site, an average shift length of less than 4 hours, and uncertainty in the pulmonary function data, are plausible explanations for the null findings, which should be interpreted with caution. We recommend that future studies measure changes in pulmonary function across multiple time intervals and consecutive days; conduct pre-shift pulmonary function assessments at earlier hours, particularly among those who sleep at the site, or compensate workers for the time that they are asked not to work prior to the pre-shift assessment; utilize a stratified recruitment strategy to include workers with varying lengths of employment and, if possible, a cohort of former e-waste recovery workers; and perform spirometry or alternative techniques for observing distal airway function in a health center using equipment that allows medical staff to review the results immediately to avoid uncertainty in the data. Alternative longitudinal study designs that estimate total or cumulative exposure and account for exposure mixtures are also needed. The challenges encountered in this study highlight how social and economic disparities that underlie the growth of informal economies[76] contribute to occupational hazards themselves. In informal sectors, where workers live and work in the same vicinity, ensuring a safe place to sleep goes hand in hand with having a safe place to work.

4.6 Figures

Figure 4-1: Sampling locations of Agobgloshie e-waste workers and Madina Zongo reference community in Accra, Ghana.



Legend: The Agobogloshie scrap and e-waste recovery site is near the South Industrial Zone and Ring Road West. The Madina Zongo residential community is approximately 15 km NE of Agbogbloshie and near the Legon East Rd (N4) in Accra, Ghana. Map created using Google Earth Pro V. 7.3.2.5776. (10 July 2015). © Google 2018.

Figure 4-2: Cross-shift sampling duration by study group among the GeoHealth cohort, Accra, Ghana, 2017-2018.

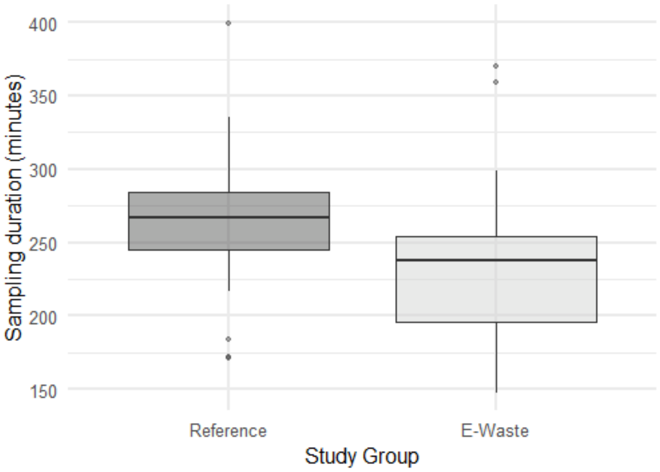


Figure 4-3: Associations between percent change in pulmonary function outcome per doubling of personal inhalation exposure to PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ for the full cohort and stratified by study group.

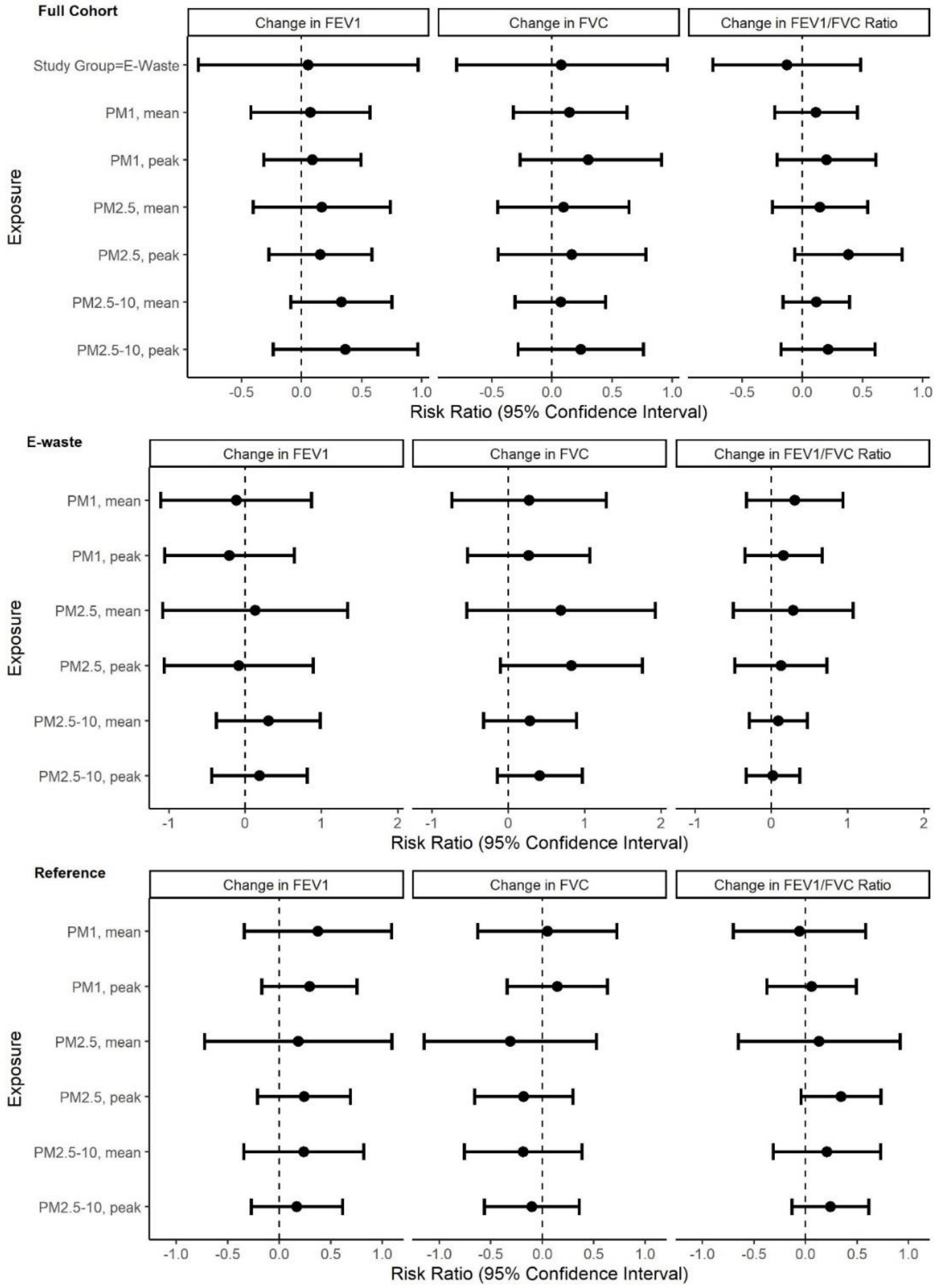


Figure 4-4: Effect of working “yesterday” on cross-shift changes in FEV1 (A) and FVC (B) percent predicted values per hour among the GeoHealth cohort, Accra, Ghana, 2017-2018.

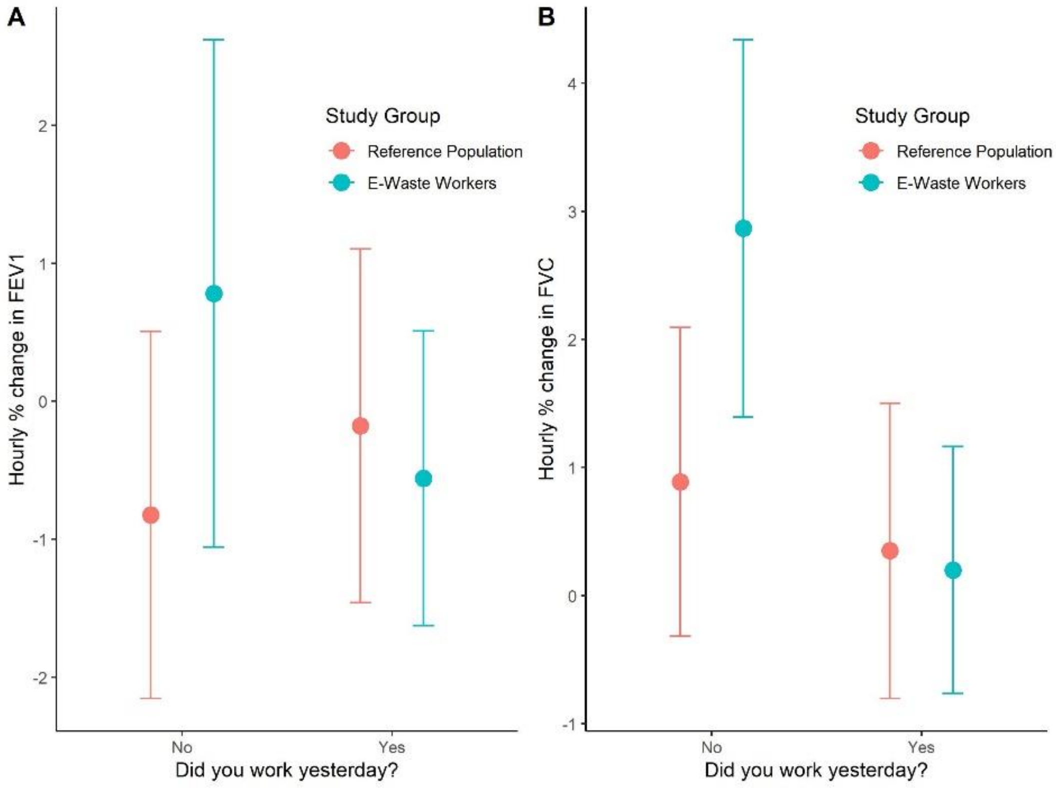
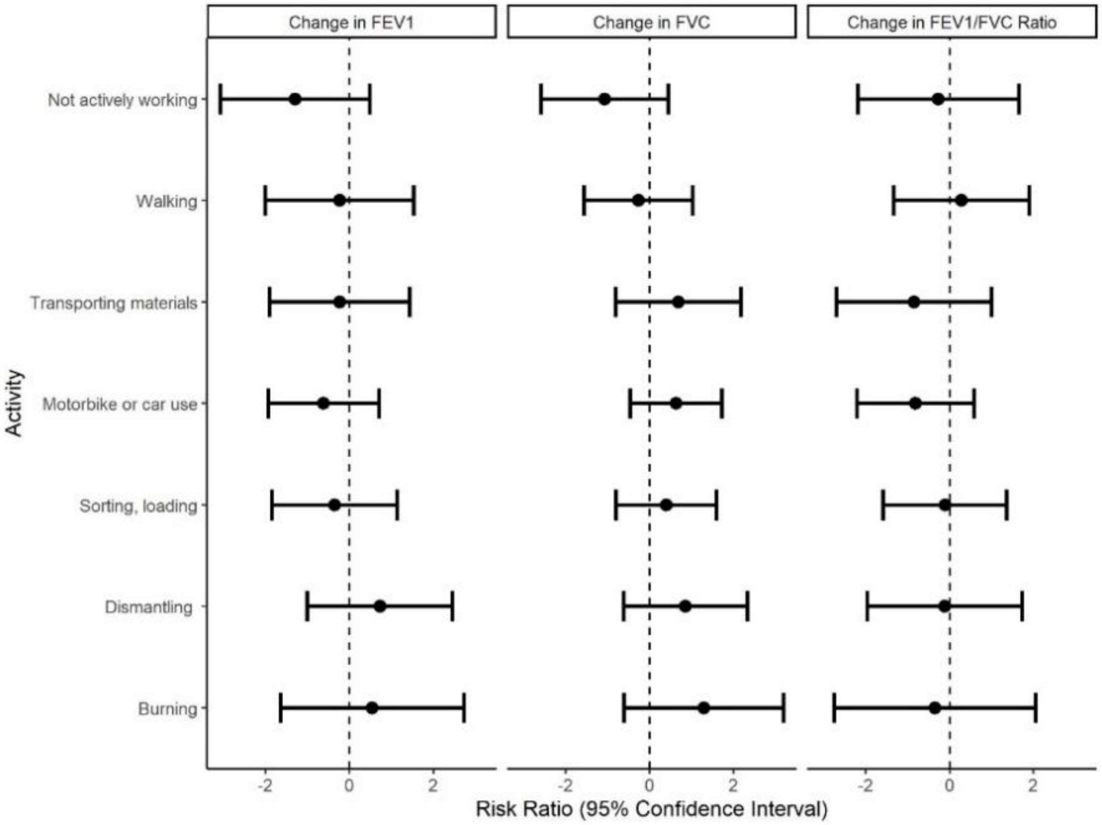


Figure 4-5: Associations between percent change in pulmonary function outcomes and performance of activities among e-waste recovery workers (n=50) in the GeoHealth cohort at Agbogbloshie, Accra, Ghana, 2017-2018.



Legend: Activities are binary variables comparing those who performed the activities to those that did not. Linear regression models included a total of 48, 40 and 38 FEV1, FVC and FEV1/FVC ratio values, respectively, and were adjusted for age, height and smoking cigarettes for the duration of the work-shift.

4.7 Tables

Table 4-1: Socio-demographics of the GeoHealth Cohort with valid cross-shift pulmonary function tests, (N=120; 73 E-waste workers and 47 members of a reference population), Accra, Ghana, 2017-2018.

Characteristic		E-waste	Reference	p-value
Sex (%)	Male	100	100	NA
Age (years) (mean (SD))		26.5 (6.6)	30.7 (9.2)	<0.01
Country of Origin (%)	Ghana	100	97.8	0.39
	Other	0	2.2	
Region of Origin (%)	Northern	100	33.3	<0.01
	Other	0	44.4	
	Accra	0	22.2	
Daily Income[a] (%)	<= GHS 20	15.1	18.6	0.23
	GHS 21-60	65.8	53.5	
	GHS 61-200	13.7	11.6	
	>200 GHS	5.5	16.3	
Religion (%)	No religion	2.7	0	0.010
	Other	2.7	17.0	
	Muslim	94.5	83.0	
Marital status (%)	Single	45.2	70.2	0.009
	Married	54.8	29.8	
Education (%)	No education	27.4	19.1	0.010
	Less than secondary	60.3	44.7	
	Secondary	12.3	29.8	
	Higher	0	6.4	
Home type (%)	Rented Room	27.4	40.4	<0.01
	Rented/owned Kiosk	43.8	6.4	
	Outdoors/Mosque	1.4	0	
	Own Home	27.4	53.2	
Use of indoor cooking (%)	Yes	16.4	51.1	<0.01
	No	83.6	48.9	
Method of cooking (%)	Open fire	0	2.2	<0.01
	Stove/Coal pot WITH vent	5.5	8.7	
	Stove/Coal pot WITHOUT vent	0	4.3	
	LPG cook stove	2.7	23.9	
	Electricity	6.8	10.9	
	Do not cook indoors	84.9	50.0	

Sleep in same room as cooking (%)	Yes	9.9	17.4	0.36
	No	90.1	82.6	
Tobacco smoke status (%)	Current	25.0	6.5	0.014
	Former	1.4	2.2	
	Never	73.6	91.3	

[a] 1 USD was equivalent to approximately 4.42 GHS at the time of the study.

Table 4-2: Self-reported respiratory health by study groups among the GeoHealth cohort, (N=120; 73 E-waste workers and 47 members of a reference population), Accra, Ghana, 2017-2018.

Self-reported Respiratory Health	E-waste	Reference	p-value
Age (years) (mean (SD))	26.5 (6.6)	30.7 (9.2)	<0.01
Height (cm) (mean (SD))	171.4 (6.7)	173.8 (7.2)	0.06
Weight (kg) (mean (SD))	70.9 (9.7)	73.2 (13.2)	0.28
Body Mass Index (mean (SD))	24.1 (2.6)	24.2 (3.7)	0.91
Asthma, ever (%)	1.4	2.2	1.00
TB, confirmed by doctor (%)	0	0	NA
Usual Cough (%)	30.1	21.3	0.39
Cough, longer than 3 months (%)	13.7	12.8	1.00
Usual phlegm production (%)	25	21.3	0.67
Phlegm production, longer than 3 months (%)	13.7	10.6	0.83
Chronic bronchitis (%)	6.8	4.3	0.70
Breathlessness when walking (%)	8.3	2.1	0.24
Severe breathlessness when walking (%)	6.9	2.1	0.40
Wheezing (%)	23.6	8.5	0.049
Chest tightness (%)	32.9	17.0	0.089
Shortness of Breath (%)	15.1	6.4	0.24

Table 4-3: Measured and self-reported exposures during the work-shift and prior to the pre-shift pulmonary function test (PFT) by study group, N=120 unique participants and N=156 work-shifts in the GeoHealth cohort, Accra, Ghana, 2017-2018.

		Total	E-waste	Reference	p-value
N work-shifts		156	92	64	
Personal inhalation exposure					
PM_1, shift mean	Median (IQR)	38.2 (33.8)	51.4 (32.2)	26.3 (12.8)	<0.001
	Mean (SD)	46.2 (27.3)	57.6 (26.4)	29.6 (18.6)	<0.001
PM_1, shift peak	Median (IQR)	104.4 (103.7)	136.7 (102.0)	54.5 (52.8)	<0.001
	Mean (SD)	123.9 (86.0)	156.1 (84.6)	76.5 (63.3)	<0.001
$PM_{2.5}$, shift mean	Median (IQR)	51.3 (37.7)	63.8 (28.9)	32.9 (10.7)	<0.001
	Mean (SD)	55.8 (27.7)	69.6 (24.8)	35.6 (17.4)	<0.001
$PM_{2.5}$, shift peak	Median (IQR)	142.1 (144.6)	173.0 (111.3)	68.5 (83.5)	<0.001
	Mean (SD)	159.5 (102.4)	195.7 (93.9)	106.6 (91.2)	<0.001
$PM_{2.5-10}$, shift mean	Median (IQR)	66.4 (51.7)	77.4 (65.5)	47.4 (34.9)	<0.001
	Mean (SD)	86.6 (75.4)	101.1 (76.9)	65.3 (68.4)	<0.001
$PM_{2.5-10}$, shift peak	Median (IQR)	221.3 (254.8)	257.5 (256.6)	170.4 (199.9)	0.004
	Mean (SD)	314.1 (283.8)	331.6 (249.0)	288.5 (328.8)	0.004
Smoked cigarettes during the shift, self-report	Yes	28	24 (85.7)	4 (14.3)	0.001
Pre-shift exposures					
Worked "yesterday" (day prior to PFT)	Yes	113	78 (69.0)	35 (31.0)	<0.001
Worked prior to pre-shift PFT (same day)	Yes	73	54 (74.0)	19 (26.0)	0.001

Table 4-4: Cross-shift pulmonary function (PF) by study group among the GeoHealth cohort (N=120 unique participants), Accra, Ghana 2017-2018.

		Overall[a]	E-waste	Reference	p-value[b]
	N matched pre- and post-shift PF tests	156	92	64	
	Age (years) (mean (SD))	28.5 (7.9)	26.7 (6.4)	31.0 (9.1)	0.01
	Height (cm) (mean (SD))	171.6 (7.0)	170.7 (6.9)	172.9 (7.0)	0.05
	Weight (kg) (mean (SD))	71.1 (11.3)	70.3 (10.1)	72.4 (12.8)	0.25
Pre-shift PF	FEV1, pre-shift (mean (SD))	3.1 (0.5)	3.0 (0.5)	3.2 (0.5)	0.06
	FEV1 % predicted (mean (SD))	86.3 (12.3)	84.9 (13.5)	88.4 (10.2)	0.08
	FEV1 % predicted <70 = yes (%)	12 (7.8)	9 (9.9)	3 (4.8)	0.39
	Best FVC, pre-shift (mean (SD))	3.8 (0.6)	3.8 (0.5)	3.7 (0.6)	0.77
	FVC % predicted (mean (SD))	90.2 (12.9)	91.6 (13.4)	88.3 (11.9)	0.15
	FVC % predicted <70 = 1 (%)	7 (5.4)	3 (3.9)	4 (7.5)	0.62
	FEV1/FVC Ratio (mean (SD))	0.8 (0.1)	0.8 (0.1)	0.8 (0.1)	0.01
	Ratio <0.7 = yes (%)	8 (6.3)	8 (10.7)	0 (0.0)	0.04
Post-shift PF	FEV1, post-shift (mean (SD))	3.0 (0.5)	2.9 (0.5)	3.1 (0.5)	0.04
	FEV1 % predicted (mean (SD))	84.5 (13.1)	82.8 (14.2)	86.9 (10.9)	0.06
	FEV1 % predicted <70 = 1 (%)	22 (14.2)	17 (18.7)	5 (7.8)	0.09
	Best FVC, post-shift (mean (SD))	3.7 (0.6)	3.7 (0.6)	3.7 (0.6)	0.83
	FVC % predicted (mean (SD))	88.2 (13.6)	89.1 (15.4)	86.8 (10.4)	0.34
	FVC % predicted <70 = yes (%)	8 (5.8)	5 (6.1)	3 (5.5)	1.00
	FEV1/FVC Ratio (mean (SD))	0.8 (0.1)	0.8 (0.1)	0.8 (0.1)	0.01
	Ratio <0.7 = yes (%)	10 (7.4)	10 (12.3)	0 (0.0)	0.02
Cross-shift change	% Change in FEV1 (mean (SD))[2]	-1.9 (8.2)	-2.2 (9.4)	-1.5 (6.4)	0.61
	% Change in FVC (mean (SD))[3]	-1.0 (6.7)	-1.2 (7.1)	-0.8 (6.0)	0.77
	% Change in FEV1/FVC ratio (mean (SD))[4]	-0.5 (4.7)	-0.8 (5.2)	-0.1 (3.9)	0.41

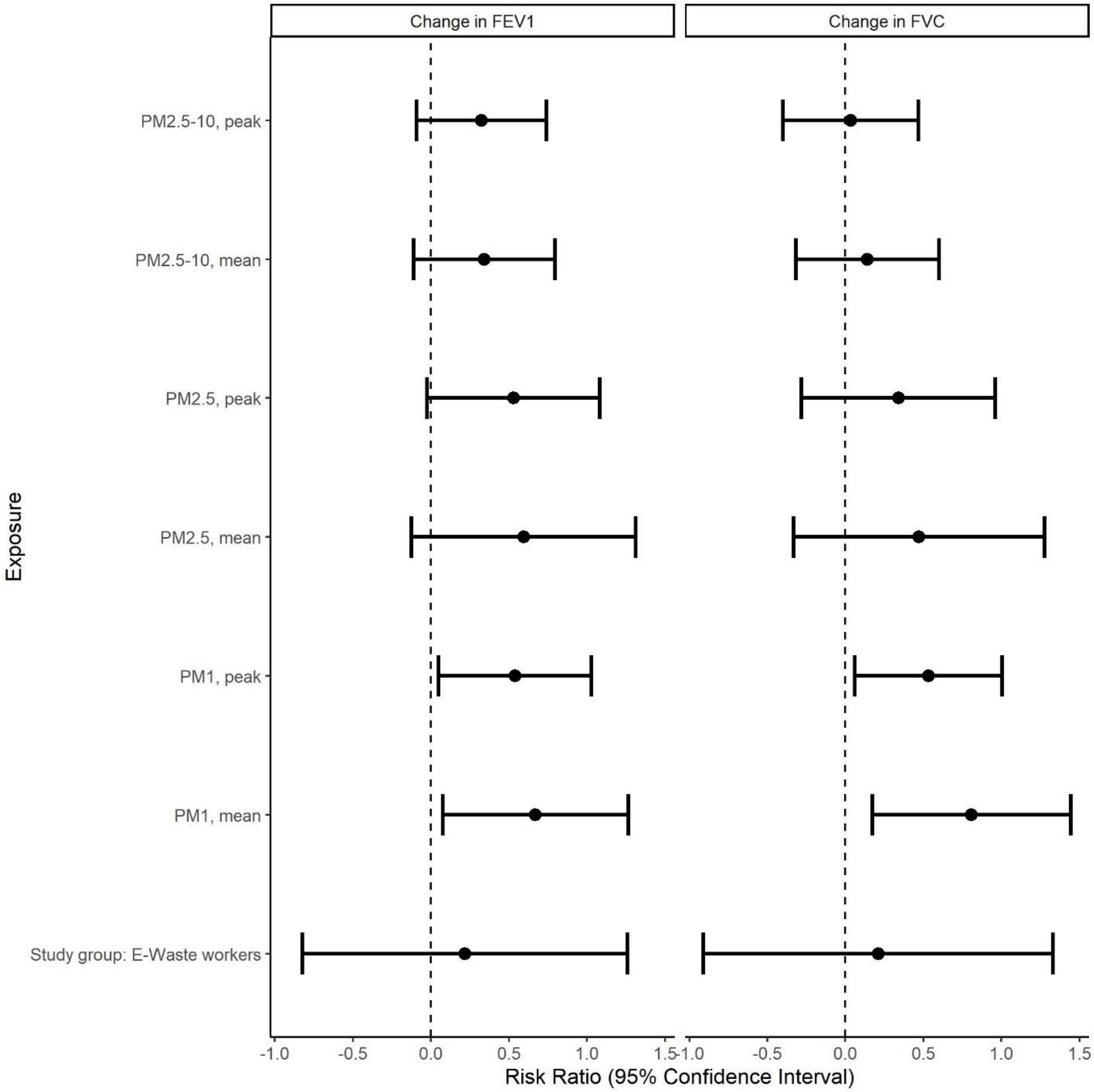
[a] Number of matched sessions with a valid pre and post-shift FEV1, FVC and FEV1/FVC ratio were 153, 123 and 120, respectively; [b] T-test p-values are comparing exposed and reference populations.

Table 4-5: Descriptive statistics on image-derived activities performed by e-waste worker participants during their monitored work shift at Agbogbloshie, Accra, Ghana, 2017-2018.

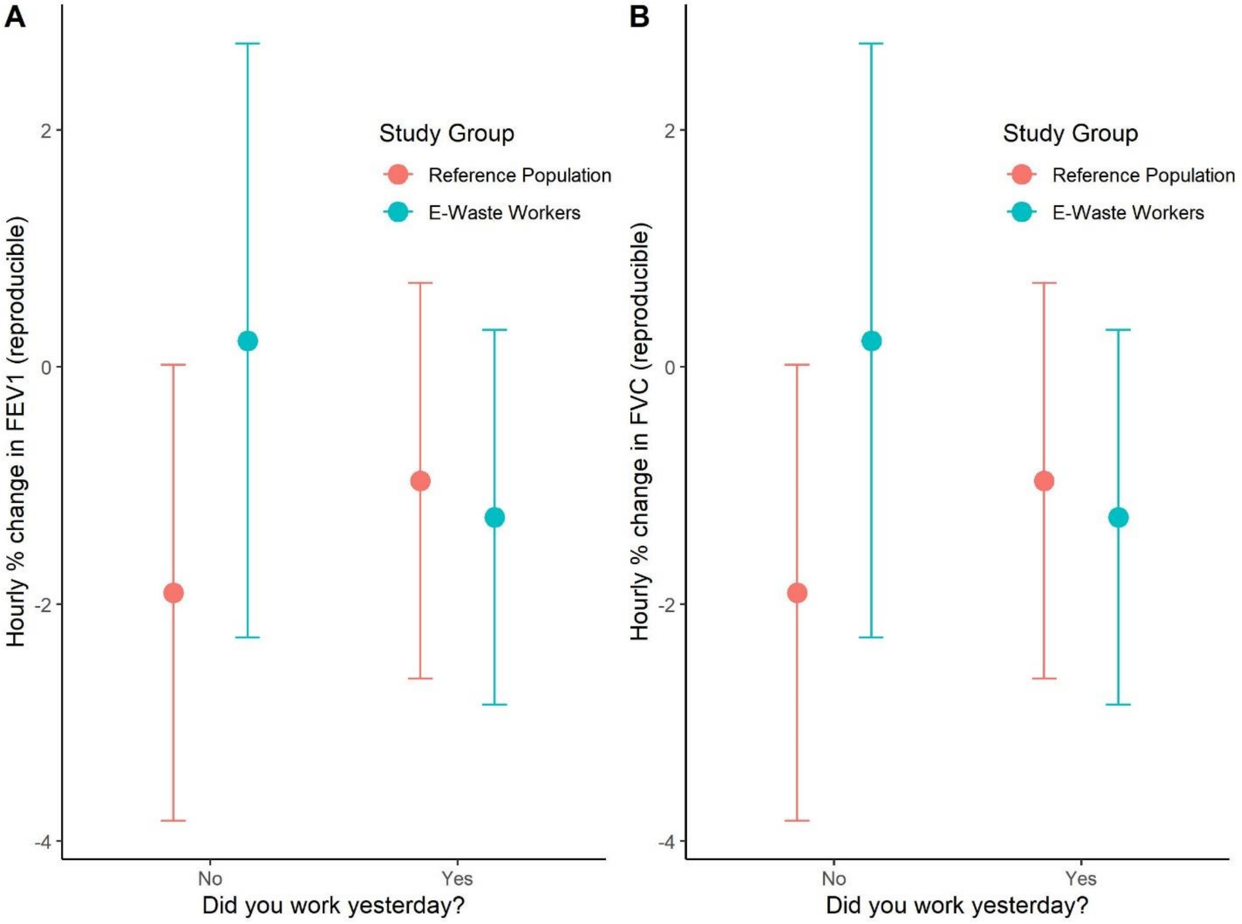
Activity	Mean duration in minutes (range)	Number of participants who performed the activity
Burning e-waste	69.6 (7, 147)	5
Dismantling e-waste	78.4 (3, 238)	8
Buying, selling e-waste	25.5 (16, 35)	2
Transporting materials	28.0 (4, 88)	8
Sorting, loading e-waste	59.7 (5, 170)	10
Motorcycle or car use	32.6 (4, 129)	17
Bicycling	29.5 (17, 37)	4
Walking	31.4 (5, 113)	45
Not actively working	105.2 (9, 225)	43
Presence of tobacco smoke	48.0 (23, 67)	3
Other, e-waste related work	69.7 (16, 116)	3
Other, non-e-waste related work	6.0 (4, 8)	2

4.8 Supplementary Tables and Figures

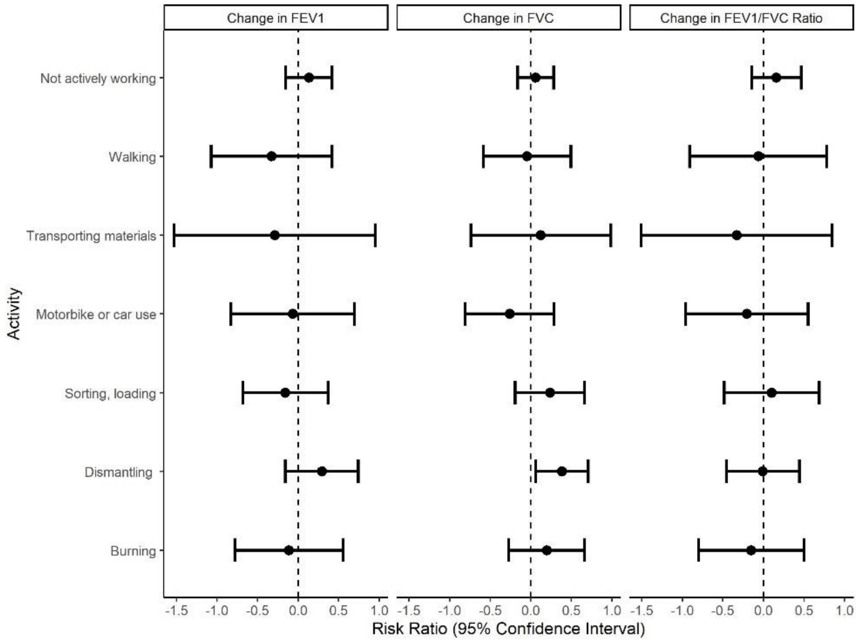
Supplemental Figure 4-1 Associations between percent change in pulmonary function outcome per doubling of personal inhalation exposure to PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ using reproducible pulmonary function data for the full GeoHealth cohort, Accra, Ghana, 2017-2018.



Supplemental Figure 4-2 Effect of working “yesterday” on cross-shift changes in FEV1 (A) and FVC (B) percent predicted values per hour using reproducible data pulmonary function data among the GeoHealth cohort, Accra, Ghana, 2017-2018.



Supplemental Figure 4-3 Associations between e-waste recovery activities (length of time spent performing the activity) and cross-shift changes in pulmonary function among e-waste recovery workers (n=50) enrolled in the GeoHealth cohort at Agbogbloshie, Accra, Ghana, 2017-2018.



Legend: Linear regression models included a total of 48, 40 and 38 FEV1, FVC and FEV1/FVC ratio values, respectively, and were adjusted for age, height and smoking cigarettes for the duration of the work-shift. A one-unit increase in activity is equivalent to performing the activity for 30-minutes.

Supplemental Table 4-1 Cross-shift pulmonary function by exposure group using reproducible results among the GeoHealth cohort, Accra, Ghana 2017-2018.

		Overall[a]	E-waste	Reference	p-value[b]
	N Pulmonary Function Tests	72	44	28	
	Age (years) (mean (SD))	28.56 (7.23)	29.61 (6.76)	26.89 (7.75)	0.12
	Height (cm) (mean (SD))	171.44 (6.80)	170.57 (5.83)	172.82 (8.01)	0.172
	Weight (kg) (mean (SD))	71.65 (11.62)	71.95 (10.00)	71.18 (13.97)	0.784
	Shift length (mean (SD))	247.43 (41.65)	234.19 (44.93)	268.23 (24.73)	<0.001
PRE-Shift	FEV1, pre-shift (mean (SD))	3.12 (0.47)	2.98 (0.42)	3.33 (0.47)	0.002
	FEV1 % predicted (mean (SD))	87.78 (11.03)	85.33 (10.92)	91.46 (10.32)	0.027
	FEV1 % predicted <70 = yes (%)	4 (6.2)	4 (10.3)	0 (0.0)	0.246
	Best FVC, pre-shift (mean (SD))	4.01 (0.59)	4.02 (0.65)	3.99 (0.51)	0.896
	FVC % predicted (mean (SD))	95.54 (12.93)	97.66 (14.28)	92.57 (10.52)	0.25
	FVC % predicted <70 = 1 (%)	0 (0.0)	0 (0.0)	0 (0.0)	NA
	FEV1/FVC Ratio (mean (SD))	0.81 (0.07)	0.77 (0.06)	0.85 (0.04)	<0.001
	Ratio <0.7 = yes (%)	2 (6.9)	2 (12.5)	0 (0.0)	0.559
POST-SHIFT	FEV1, post-shift (mean (SD))	3.06 (0.48)	2.95 (0.45)	3.23 (0.47)	0.017
	FEV1 % predicted (mean (SD))	85.88 (11.95)	84.22 (12.23)	88.38 (11.29)	0.171
	FEV1 % predicted <70 = 1 (%)	7 (10.8)	6 (15.4)	1 (3.8)	0.288
	Best FVC, post-shift (mean (SD))	3.95 (0.61)	3.97 (0.67)	3.91 (0.52)	0.747
	FVC % predicted (mean (SD))	93.78 (13.25)	96.64 (14.52)	89.78 (10.41)	0.127
	FVC % predicted <70 = yes (%)	0 (0.0)	0 (0.0)	0 (0.0)	NA
	Fev1/FVC Ratio (mean (SD))	0.80 (0.06)	0.77 (0.06)	0.85 (0.04)	<0.001
	Ratio <0.7 = yes (%)	2 (6.9)	2 (12.5)	0 (0.0)	0.559
Change	% Change in FEV1 (mean (SD))[2]	-1.85 (6.31)	-1.10 (6.19)	-2.96 (6.45)	0.249
	% Change in FVC (mean (SD))[3]	-1.52 (5.31)	-1.16 (4.99)	-2.02 (5.87)	0.639
	% Change in FEV1/FVC ratio (mean (SD))[4]	0.01 (2.29)	0.41 (2.28)	-0.48 (2.29)	0.306

[a] Number of matched sessions with a valid pre and post-shift FEV1, FVC and FEV1/FVC ratio were 65, 35, 29, respectively; [b] T-test p-values are comparing exposed and reference populations.

Supplemental Table 4-2: Associations between percent change in pulmonary function outcome per doubling of personal inhalation exposure to PM$_1$, PM$_{2.5}$ and PM$_{2.5-10}$ for the full GeoHealth cohort, Accra, Ghana 2017-2018.

		ΔFEV1 (% change / hour)^a	ΔFVC (% change / hour)^b	ΔRatio (% change / hour)^c
	Model specification	RR (95%CI)	RR (95%CI)	RR (95%CI)
Main effects of exposure group and PM				
PM$_1$, mean	crude	0.07 (-0.39 to 0.54, p=0.765)	0.17 (-0.28 to 0.62, p=0.457)	0.01 (-0.31 to 0.32, p=0.968)
	+ covariates^d	0.07 (-0.45 to 0.58, p=0.791)	0.09 (-0.40 to 0.58, p=0.724)	0.11 (-0.23 to 0.46, p=0.516)
PM$_1$, peak	crude	0.03 (-0.35 to 0.40, p=0.877)	0.12 (-0.24 to 0.48, p=0.517)	0.01 (-0.24 to 0.27, p=0.921)
	+ covariates	0.09 (-0.33 to 0.51, p=0.668)	0.10 (-0.30 to 0.49, p=0.617)	0.14 (-0.14 to 0.41, p=0.334)
PM$_{2.5}$, mean	crude	-0.00 (-0.53 to 0.53, p=0.999)	0.02 (-0.49 to 0.53, p=0.939)	0.07 (-0.29 to 0.42, p=0.717)
	+ covariates	0.17 (-0.43 to 0.76, p=0.580)	0.09 (-0.47 to 0.66, p=0.743)	0.15 (-0.25 to 0.54, p=0.462)
PM$_{2.5}$, peak	crude	-0.01 (-0.39 to 0.37, p=0.955)	0.01 (-0.36 to 0.37, p=0.977)	0.13 (-0.13 to 0.38, p=0.329)
	+ covariates	0.16 (-0.29 to 0.61, p=0.480)	0.08 (-0.33 to 0.50, p=0.692)	0.25 (-0.04 to 0.54, p=0.091)
PM$_{2.5-10}$, mean	crude	0.30 (-0.10 to 0.69, p=0.139)	0.09 (-0.27 to 0.45, p=0.623)	0.09 (-0.16 to 0.35, p=0.463)
	+ covariates	0.33 (-0.11 to 0.77, p=0.138)	0.11 (-0.28 to 0.50, p=0.580)	0.12 (-0.16 to 0.39, p=0.408)

$PM_{2.5-10}$, peak	crude	0.24 (-0.10 to 0.59, p=0.164)	0.18 (-0.13 to 0.49, p=0.251)	0.10 (-0.12 to 0.32, p=0.384)
	+ covariates	0.23 (-0.17 to 0.64, p=0.249)	0.17 (-0.18 to 0.53, p=0.339)	0.14 (-0.11 to 0.39, p=0.281)
Exposure Group (ref=reference population)	crude	-0.28 (-1.01 to 0.46, p=0.454)	-0.11 (-0.81 to 0.58, p=0.747)	-0.20 (-0.70 to 0.30, p=0.433)
	+ covariates	0.06 (-0.88 to 1.01, p=0.897)	0.04 (-0.84 to 0.91, p=0.935)	-0.12 (-0.75 to 0.51, p=0.701)
	+ exposure Group* PM1, mean	-0.45 (-1.75 to 0.84, p=0.488)	0.47 (-0.73 to 1.66, p=0.441)	-0.03 (-0.90 to 0.84, p=0.943)
	+ exposure Group* PM1, peak	-0.45 (-1.47 to 0.56, p=0.376)	0.33 (-0.60 to 1.27, p=0.480)	-0.17 (-0.83 to 0.49, p=0.605)
	+ exposure Group* PM2.5, mean	0.07 (-1.55 to 1.70, p=0.930)	1.14 (-0.36 to 2.63, p=0.133)	-0.06 (-1.15 to 1.04, p=0.918)
	+ exposure Group* PM2.5, peak	-0.09 (-1.14 to 0.97, p=0.873)	1.08 (0.07 to 2.08, p=0.036)	-0.27 (-0.97 to 0.43, p=0.442)
	+ exposure Group*$PM_{2.5-10}$, mean	0.17 (-0.90 to 1.23, p=0.759)	0.53 (-0.38 to 1.45, p=0.247)	-0.17 (-0.86 to 0.52, p=0.622)
	+ exposure Group* $PM_{2.5-10}$, peak	0.20 (-0.66 to 1.06, p=0.648)	0.61 (-0.17 to 1.38, p=0.122)	-0.31 (-0.85 to 0.24, p=0.268)
Pre-Shift Exposures				
Worked yesterday (day before the PF test) , (ref=No)	crude	-0.34 (-1.17 to 0.50, p=0.428)	-0.77 (-1.55 to 0.02, p=0.055)	0.16 (-0.41 to 0.74, p=0.571)
	+ covariates	-0.19 (-1.20 to 0.82, p=0.712)	-1.22 (-2.18 to -0.27, p=0.013)	0.57 (-0.13 to 1.27, p=0.111)

		+ worked yesterday*exposure group	-2.01 (-4.02 to 0.01, p=0.051)	-1.79 (-3.57 to -0.02, p=0.048)	-0.26 (-1.58 to 1.06, p=0.696)
	Worked prior to the pre-shift PF test (same day), (ref=No)	crude	-0.21 (-0.94 to 0.52, p=0.569)	-0.24 (-0.92 to 0.44, p=0.488)	-0.32 (-0.81 to 0.17, p=0.193)
		+ covariates	-0.07 (-0.88 to 0.74, p=0.861)	0.05 (-0.70 to 0.80, p=0.892)	-0.35 (-0.89 to 0.18, p=0.191)
		+ worked prior*exposure group	0.48 (-1.29 to 2.26, p=0.591)	-0.34 (-1.99 to 1.30, p=0.682)	-0.19 (-1.37 to 0.99, p=0.747)

[a] Number of sessions with a valid pre and post-shift FEV1 and personal PM monitoring data = 151; [b] Number of participants with a valid pre and post-shift FVC and personal PM monitoring data = 123; [c] Number of participants with a valid pre and post-shift Ratio and personal PM monitoring data = 118; [d] Covariates in the adjusted models include age, height, use of cigarettes during the shift, wave of data collection and day of week.

Supplemental Table 4-3 Stratified analysis of the association between pulmonary function (cross-shift and percent predicted) and working "yesterday" (the day before pulmonary function testing) in E-waste workers (n=90) and a reference population (n=64) enrolled in the GeoHealth Cohort, Accra, Ghana, 2017-2018.

	E-Waste Workers (n=90 work-shifts)			Reference Population (n=64 work shifts)		
	ΔFEV1 (% change / hour)	FEV1 pre-shift % predicted	FEV1 post-shift % predicted	ΔFEV1 (% change / hour)	FEV1 pre-shift % predicted	FEV1 post-shift % predicted
Work Yesterday (ref=No)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)
crude	-1.31 (-3.03, 0.42)	-5.61 (-14.26, 3.03)	-8.95 (-17.99, 0.09)	0.38 (-0.36, 1.13)	1.62 (-3.57, 6.80)	3.05 (-2.40, 8.50)
+ covariates[a]	-1.19 (-3.07, 0.69)	-9.21 (-18.04, -0.38)	-12.07 (-21.36, -2.78)	0.28 (-0.62, 1.18)	0.68 (-6.56, 7.92)	2.24 (-5.30, 9.78)
	ΔFVC (% change / hour)	FVC pre-shift % predicted	FVC post-shift % predicted	ΔFVC (% change / hour)	FVC pre-shift % predicted	FVC post-shift % predicted
Work Yesterday (ref=No)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)	RR (95%CI)
crude	-1.69 (-3.15, -0.23)	0.96 (-8.05, 9.98)	-4.74 (-15.09, 5.60)	-0.16 (-0.97, 0.65)	5.03 (-1.56, 11.61)	4.07 (-1.56, 9.70)
+ covariates[a]	-2.43 (-4.04, -0.81)	0.70 (-8.81, 10.21)	-6.49 (-17.37, 4.38)	-0.25 (-1.30, 0.79)	4.32 (-5.18, 13.82)	4.18 (-3.12, 11.49)

[a] Covariates in the adjusted models include age, height, use of cigarettes during the shift, wave of data collection and day of week.

Supplemental Table 4-4 Incident respiratory symptoms reported among e-waste and reference population study participants (N=156 work shifts; 92 E-waste worker shifts and 47 reference population shifts) enrolled in the GeoHealth cohort, Accra, Ghana, 2017-2018.

Incident symptom	E-waste worker	Reference population	p-value
Irritation or burning of the eyes, nose or throat (%)	13.0	14.1	1
Chest tightness or a sensation of a band around the chest (%)	9.8	3.1	0.2
Cough (%)	17.4	11.1	0.36
Shortness of breath, difficulty catching your breath, or a smothering feeling (%)	9.8	6.2	0.56
Wheezing or whistling sound in your chest apart from colds (%)	16.3	7.8	0.15

5 Chapter 5: Conclusions

5.1 Summary of Main Findings

The primary aims of this dissertation were to: (1) design and validate a method of using wearable cameras to derive a highly time-resolved source of time-activity data; (2) identify high-risk worker groups by establishing task-specific breathing zone concentrations to PM air pollution by combining the image-derived time-activity data with continuous and contemporaneous measures of personal PM concentrations; and lastly, (3) examine the association between personal inhalation exposure to PM and cross-shift changes in pulmonary function among e-waste workers and a comparison population. The findings presented in this dissertation have contributed to the limited data on occupational exposure to air pollution and respiratory health effects from e-waste recovery practices and may inform the development of risk-mitigating strategies for reducing exposure to inhalation hazards. Further, the findings describe and validate a method of deriving image-based time activity data applicable to other informal and non-traditional work settings with similar job and exposure characteristics.

Chapter 2 addressed the need for highly time-resolved activity data that can be used to establish task-specific concentrations in an informal work setting with acute (<5 min) peak exposures. The most common method used to derive time-activity data is hand-written diaries; previous studies that relied on time-activity diaries with as low as a 15-minute time-resolution were unable to detect significant differences in exposures across job categories[20,25,26,28]. This may be due to a lack of precision, misclassification, or both. We classified over 32,000 time-lapse images (one image per minute) from 170 partial work-shifts among e-waste recovery workers; reviewed image-classifications with workers in interviews; examined the agreement with hand-written diaries; and, described levels of personal PM exposure for unique work-, transportation- and non-work-related activities. Using the image-based activity data, we observed high variability in activity types and duration, and, low to no agreement with self-reported diaries. Among all activities, burning e-waste was associated with the highest mean concentrations of $PM_{2.5}$ (202.8 µg m^{-3}), followed by dismantling (89 µg m^{-3}) and sorting/loading (82.8 µg m^{-3}) e-waste. Unexpectedly, we found that workers spend a large portion of time on the e-waste site not actively working (54% of the time sampled in our study). During this time, mean personal $PM_{2.5}$ concentrations (72.7 µg m^{-3}) exceeded concentrations during some work activities (i.e., buying, selling and repairing e-waste) and the WHO's 24-hour ambient $PM_{2.5}$ target of 25 µg m^{-3}. Our findings suggest that image-based time-activity data from wearable cameras can substantially improve occupational exposure assessments in informal settings by providing a level of task and time precision that hand-written diaries cannot achieve.

Chapter 3 built upon the descriptive task-specific exposure data generated in Chapter 2 by estimating relative levels of personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ associated with e-waste recovery and examining effect modification by wind conditions. Regardless of activity, the mean personal $PM_{2.5}$ (80 µg m^{-3}) and $PM_{2.5\text{-}10}$ (125 µg m^{-3}) concentrations, adjusted for predicted concentrations of background $PM_{2.5}$, study wave, day of week, temperature and humidity, were found to considerably exceed existing ambient air quality guidelines for $PM_{2.5}$ and $PM_{10.}$ In comparison to when workers were on- site, but not actively working, burning and the use of tobacco products were associated with the largest increases in $PM_{2.5}$ exposure, (28% and 22%, respectively). Transportation-related activities (e.g., bicycling, motorbike or car use), however, were associated with larger increases in $PM_{2.5\text{-}10}$ than many of the work activities, including dismantling, sorting/loading and buying or selling e-waste. In analysis of effect modification by wind direction and wind speed, we found a positive association between wind direction variability and personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ among workers burning e-waste and a positive association between wind speeds and personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ among those dismantling e-waste. Adding to anecdotal evidence, these findings suggest that burners have a harder time avoiding smoke exposure when wind direction is variable. Further, they suggest that plumes of smoke travelling from the e-waste burn pit may be a source of PM exposure among workers positioned downwind of the burn pits and in the plume's trajectory. Safe and efficient methods of metal extraction that eliminate the need to burn e-waste will likely elicit the greatest reductions in personal occupational and community-level exposure to PM air pollution.

Chapter 4 incorporated pre- and post-shift pulmonary function assessments using spirometry in order to examine acute respiratory related health effects associated with concomitant personal PM exposure (sizes <1, <2.5 and the coarse fraction, $_{2.5\text{-}10}$ µm in aerodynamic diameter) among e-waste workers and a comparison population living in Accra, Ghana. We found that personal PM concentrations (all sizes) among e-waste workers were nearly twice as high as those observed among the reference population. However, mean personal $PM_{2.5}$ among the reference population (35.6 ± 17 µg m^{-3}) still exceeded recommended levels established by the WHO (24-hour mean: 25 µg m^{-3}). Potential sources of PM exposure may include traffic-related air pollution and smoke from cooking food. Both populations had unadjusted declines in pulmonary function after an average of 4 hours of exposure; percent decreases in FEV1 and FVC per hour were greater among e-waste workers (2.2 % ± 9.4 and 1.2 % ± 7.1, respectively) than the reference population (1.5 % ± 6.4 and 0.8 % ± 6.0, respectively), but the differences did not reach statistical significance at the 0.05 alpha level. Unexpectedly, cross-shift changes in pulmonary function were not associated with personal PM (all sizes) exposure. And, pulmonary function was not associated with e-waste recovery activities. Possible explanations for these findings include: Selection bias due to the "healthy worker" effect and exclusions among e-waste worker participants who failed to perform valid spirometry maneuvers; the average length of employment in our sample (8 years) being too long to capture decrements in lung function associated with a worker's initial months or years of employment; and shift duration being too short. Most notable, however, was the inability to capture a true baseline (pre-shift) pulmonary function assessment among e-waste worker participants who live on-site (89%). We did observe steeper declines in FVC and FEV1 throughout the shift among e-waste worker participants who reported working the day before in comparison to those that did not. These results are suggestive of a potential lagged effect of e-waste-associated PM pollution on respiratory health. We hope that future studies can achieve a greater degree of reliability and precision in their results by learning from the challenges we encountered and following our recommendations for conducting similar studies in informal job settings.

5.2 Key strengths and limitations

The development of a method to derive an objective and highly time-resolved source of time-activity data using wearable cameras in an informal setting is a key strength of Chapter 2. The combination of image-derived activity data with continuous and contemporaneous measures of size-specific PM to establish relative levels of personal inhalation exposure to $PM_{2.5}$ and $PM_{2.5-10}$ across activities performed by e-waste workers during a partial work shift is a strength of chapters 2 and 3. Additional strengths of chapter 3 include the use of available meteorological data to both estimate background concentrations of $PM_{2.5}$ and examine potential downwind effects of smoke plumes from e-waste burn pits; and, the inclusion of a discussion on challenges and opportunities associated with instituting a hierarchy of air quality controls in an informal work setting. Lastly, the application of a gold-standard, cross-shift study design in an informal setting is a strength of chapter 4. The use of spirometry, a highly sensitive physiological measure of pulmonary function, and personal measures of PM air quality among e-waste workers and Accra residents will add to the limited available information on pulmonary function and emission sources in Ghana. We examined the effects of both daily mean and peak PM concentrations, the magnitudes of which are unique to e-waste recovery, on pulmonary function. With the hope of improving reliability and precision, chapter 4 provided recommendations for conducting similar studies in informal settings.

The key limitations of chapter 2 are the time-intensive nature of the task of manually categorizing time-lapse images and the lack of location data to confirm that all activities occurred on the e-waste site. The exploratory nature of our study required manual review of images. However, new machine learning and artificial intelligence methods for image categorization will make the use of time-lapse images more accessible for future investigators. In Chapter 3, unknown measurement error associated with the use of fitted rather than observed measures of background $PM_{2.5}$ may have resulted in over- or under-estimates of relative risks of personal PM exposure by job activity. Moreover, the use of meteorological data from a nearby airport (10.2 km from the Agbogbloshie e-waste site) may not have accurately reflected the microclimate at Agbogbloshie. Limitations of chapter 4 included: significant differences in most socio-demographic characteristics between the e-waste workers and reference population, (e.g., prevalence of current smokers and use of indoor cooking); potential selection bias due to the exclusion of a high number of e-waste worker participants who failed to perform a valid spirometry maneuver; the inability to perform pre-shift pulmonary function tests among e-waste workers who sleep on the e-waste site; and the lack of an inception cohort to examine potential early decrements in pulmonary function that may flatten out with increased length of employment.

5.3 Next Steps

The findings of this dissertation have helped identify numerous paths forward and serve as a jumping off point for the design of interventions aimed at reducing occupational and community-level exposure to air pollution from e-waste recovery practices.

This dissertation laid the groundwork for deriving image-based time-activity data in a non-traditional work setting using low-cost wearable cameras. Advances to the method (i.e., automated image-classification and addition of location data) will make it more accessible for future occupational and larger population-based studies utilizing big data. Careful attention to the ethical implications of using image and location data, however, need to be considered. In categorizing images, we identified many women working near the e-waste burn pits. Women were previously known to work on the e-waste site selling food and water. However, it was not previously known that they stand for long periods of time near the burning area to sell water for the purpose of cooling copper after it is removed from the fires. Women and children are arguably the most vulnerable to the health consequences from e-waste associated pollutants and should be included in future studies and targeted in education campaigns on the dangers of exposure to lead, POPs, and other e-waste associated pollutants. We recommend that the images be used in deriving educational materials for workers and populations living near the site.

Interventions aimed at reducing personal PM exposure from burning activities and follow-up studies of their effectiveness are needed. Burning activities are the source of the highest personal PM exposure not only for workers performing the burning, but perhaps also for workers located downwind of the burn-pits. Reductions in the large amount of time that workers spend on the site when not actively working (over 50% of the time observed in our sample) can further eliminate unnecessary exposures. Efforts to reorganize the worksite and methods require cooperation between workers, local leaders, and multidisciplinary teams of engineers, exposure experts, epidemiologists, and social scientists. A focus should be the design of innovative technologies that can balance pollution reductions with job availability. Furthermore, to follow-up on the apparent lack of work identified through image classification, studies examining the health burden related to psycho-social stressors of the job, under-employment and effort-reward imbalances are needed.

Future studies aimed at evaluating levels of PM toxicity from e-waste recovery practices will inform assessments of relative risk from inhalation. PM from e-waste activities may be more toxic than PM from traffic-related emissions or from indoor cooking due to its potentially high fraction of PAHs, dioxins, flame retardants and metals[101]. Higher levels of toxicity may have significant consequences for the community health burden posed by e-waste associated air pollution. PM dispersion models can build on the preliminary analysis of effect modification by wind conditions by incorporating a worker's location. In addition, dispersion models can be used to evaluate the risk of downwind, community-level health effects.

Further investigation of acute and chronic respiratory health conditions associated with occupational exposure to airborne pollutants from e-waste recovery appears warranted. Alternative longitudinal study designs that estimate total or cumulative exposure and account for exposure mixtures are a next step. Future studies using data generated by the GeoHealth study that measure changes in pulmonary function over time (i.e. consecutive work days, weeks or months) will provide useful insight into respiratory health and potential lagged effects of e-wasted associated PM exposure. Future applications of cross-shift studies should ensure that pre-shift pulmonary function assessments can be performed before exposure to dust or smoke from the worksite; this may mean restricting eligibility to workers who live off site or compensating workers for the time they are not working before the assessment. Stratified recruitment of workers based on length of employment will contribute valuable information on whether decrements in lung function are associated with new rather than seasoned workers. If possible, studies among former e-waste recovery workers who may have left the site due to health problems would minimize "healthy worker" selection bias and can be used to evaluate semi-acute and chronic respiratory conditions with longer latency periods. Lastly, in our study, the reference population reported a high prevalence of respiratory health symptoms and had peak personal $PM_{2.5}$ and $PM_{2.5\text{-}10}$ concentrations that reached 106.6 (± 91.2) and 288.5 (± 328.8) $\mu g\ m^{-3}$, respectively. Future work to derive image-based time activity data for the reference population will help identify sources of inhalation exposure among Accra residents.

5.4 Public Health Significance

The significance of this work extends beyond the Agobogloshie e-waste site. There is a limited understanding of the occupational health risks among the estimated 2 billion informal workers around the globe[76]. Even in high-income countries such as the United States, non-standard work arrangements (e.g., on-call, temporary, task-based) are increasing, and workers in such arrangements do not receive health and safety training and lack bargaining rights, economic protections and job security[176]. Existing methods for evaluating the occupational health risks among workers in precarious forms of employment need to be adapted and, in some cases, reinvented from those typically used in formal occupational settings. Our demonstration of how to use wearable cameras to generate precise and objective time-activity data in place of hand-written time-activity diaries contributes to filling this gap. We hope that low-cost wearable cameras combined with low-cost technology to monitor continuous measures of exposure, such as noise, will be used in other non-traditional work settings where little information on workflow, high-risk activities and key sources of hazards is available.

The amount of e-waste generated globally is growing rapidly[74]. Many countries have taken steps to ensure proper e-waste management and minimize the use of hazardous substances in the design phase[4,133]. However, informal e-waste economies in LMICs, particularly Nigeria, Thailand, and , are still thriving[10,74]. Up- and down-stream solutions to mitigate occupational and environmental health risks from the mining, manufacturing and recycling of electronics are urgently needed. The evidence generated in this dissertation on the extreme levels of personal PM exposure among e-waste workers should be leveraged to promote adherence to standards on extended producer responsibility, product stewardship and environmental-design among electronic and electrical equipment manufacturers. Furthermore, consumer awareness of the risks associated with improper e-waste disposal can reduce the amount of e-waste that enters the municipal waste stream by motivating environmentally and socially conscious consumers to dispose of e-waste at registered collection facilities. A degree of transparency in where and how these collection facilities process the collected e-waste will further motivate consumer behavior.

The risk-mitigating strategies discussed in this dissertation to address the immediate health and safety needs of e-waste workers at Agbogbloshie are applicable to other informal e-waste sites with similar practices. A focus on innovative technologies, designed in part by workers themselves, can help eliminate the need to burn e-waste and substantially reduce exposure to air pollutants for workers on the site and those in the plume's trajectory. Moreover, it is not uncommon for other informal work settings, including used lead-acid battery smelting and small-scale mining, to perform work activities in their own backyards putting themselves and family members at risk[177,178]. Our demonstration of high personal PM exposures among workers when eating, drinking or talking on the cell phone and not actively working emphasizes the importance of separating work activities from life activities wherever possible. Health and safety training and educational campaigns to inform workers and those living nearby of the dangers associated with exposure to e-waste associated pollutants is a first step in reducing unnecessary exposures. Education, however, must coincide with comprehensive approaches to addressing disparities in housing, income, education and employment. Agbogbloshie e-waste workers who sleep on the e-waste site and in the neighboring informal settlement, "old fadama", do so out of necessity[79].

Lastly, the burden of PM air pollution disproportionately affects individuals in LMICs[57]. Yet, there is limited data on background levels of ambient air pollution or occupational exposure to PM in these settings. The measures of personal inhalation exposure to PM (sizes ≤ 1, ≤ 2.5 and coarse fraction, $_{2.5\text{-}10}$ µm in aerodynamic diameter) among workers and residents, in addition to the estimates of background $PM_{2.5}$, contributed to filling this research gap. An improved understanding of sources of personal PM exposure among e-waste workers and residents living in Accra can inform air quality management. Furthermore, many of the population-based studies that have helped establish the health-related impacts of PM air pollution are based in the United States and Europe, where daily concentration levels of PM are lower than those typically experienced in LMICs[56]. Short-term exposure to concentrations of $PM_{2.5}$ that reach levels as high as 1000 µg m^{-3} , as observed in our data, may elicit a different biological response than exposure to concentrations with less variability. This work examined associations between peak concentrations of PM and pulmonary function.

5.5 Conclusion

This dissertation has provided substantial evidence of hazardous levels of personal inhalation exposure to PM_1, $PM_{2.5}$ and $PM_{2.5-10}$ from e-waste recovery activities among informal workers in Ghana. Image-based time-activity data taught us that workers perform multiple e-waste recovery activities throughout the day, including dismantling, sorting, loading, transporting and, burning e-waste, with little to no separation from life activities (i.e., eating, drinking, and cell phone use). The average concentration of personal inhalation exposure to $PM_{2.5}$ among workers (81 µg m^{-3}) was three times higher than the target $PM_{2.5}$ ambient air quality guideline established by the WHO. Burning, followed by dismantling and sorting e-waste stood out as the recovery activities associated with the highest concentrations of PM_1, $PM_{2.5}$ and $PM_{2.5-10}$. Equally as alarming, however, was the highly polluted air that workers breathe even when eating or drinking on the worksite. Our evidence suggested that smoke from e-waste burn pits are a source of exposure among down-wind workers located in the plume's trajectory. The acute respiratory related health effects due to exposure to PM air pollution among e-waste workers remain unclear; significant challenges that we encountered when measuring changes in lung function associated with exposure to PM from e-waste activities limited our ability to draw reliable conclusions. Cross-shift study designs are useful for generating robust causal evidence in traditional work settings. However, they need to be adapted to informal settings where workers do not "clock-in" at the start of a shift. The lack of strong evidence demonstrating an association between PM from e-waste recovery and respiratory health effects in this study does not preclude our responsibility to protect workers by taking anticipatory actions. As we continue to adapt methods to evaluate the health and safety risks of informal workers, available evidence must be incorporated into the design of risk-mitigating strategies and long-term solutions.

Preventive actions, such as the development of innovative, low-cost technologies, designed in part by the workers themselves, which eliminate the need to burn e-waste, will undoubtedly improve air quality for the workers and communities living nearby. The assurance of physical, economic and social protections for e-waste recovery workers is a necessary component of an improved infrastructure for the collection, recovery and disposal of the rapidly increasing mass of e-waste generated annually around the globe.

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