



## Occupational determinants of physical activity at work: Evidence from wearable accelerometer in 2005–2006 NHANES

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### ARTICLE INFO

#### Keywords:

Occupation  
Physical activity  
Accelerometry  
Health

### ABSTRACT

Occupation determines workers' physical activity (PA) in the workplace, an important health behavior contributing to health outcomes. However, self-reported measure limits our understanding of how occupational tasks differentiate workers' PA in terms of the type, frequency, intensity, and duration. In addition, accurate estimation of occupation-based PA during workers' actual working hours requires precise work schedule information. To address these limitations, this study employs data on accelerometer-monitored PA and work schedule from the 2005–2006 National Health and Nutrition Examination Survey (NHANES). It asks two questions: How do occupations determine PA among regular daytime workers in the United States? Second, how large a share of PA difference between two occupations is attributable to differences in the implicit occupational tasks, relative to workers' demographic, health preconditions, and socioeconomic attributes? Calculating PA during the 9-to-5 period among daytime regular workers on weekdays and conducting Blinder-Oaxaca decomposition analysis, we yield insights into the occupational determinant of both PA volume (total activity counts) and fragmentation (bouts of activities). Worksite health promotion can utilize the objective occupation-PA link and design occupation-tailored interventions, which is currently underdeveloped in the United States. Moreover, our findings shed light on the physical nature of occupation, suggesting a fruitful step to reconcile the documented mixed findings on occupation-based PA and health outcomes in future studies.

### 1. Introduction

Workers' occupation defines work activity that is closely related to the levels and intensities of physical activity (PA) and health outcomes. PA during working hours serves as a bridge in the occupation-health nexus. In this paper, we consider occupation to be one of social determinants of health. While restaurant workers typically move frequently for food preparation and serving, computer scientists often sit long hours in front of a computer. In recent decades, technological advances, computerization of the workplace, and the shift from manufacturing to service-oriented occupations have profoundly transformed occupational tasks and the physical movement to undertake these tasks (Brownsen et al., 2005; Ruggie 2015; Martinez, 2019; Green, 2012). The rise of nonstandard, irregular work schedule (Gerstel & Clawson, 2018; Schneider & Harknett, 2019) further complicates the

accurate measure of occupation-based PA during working hours. Investigating the occupational determinants of workers' PA at work helps understand the impact of contemporary occupation on health and inform policy interventions for population health.

In line with "contextualizing risk factors" from social determinants of health (Link & Phelan, 1995; Phelan et al., 2010) and the ecological model of health behavior (Hadgraft et al., 2018), we conceptualize occupation as one critical context for PA. Specifically, occupational tasks require the physical abilities to perform that occupation, where the specific occupation determines the duration, frequency, and intensity of those physical actions (e.g., frequent movement, long bouts of low-intensity activity, and prolonged sedentary behavior). However, previous studies have found mixed effects of occupation-based PA on workers' health: while occupation involving excessive PA are found to be detrimental for health (Hallman et al., 2017; Krause et al., 2015), the

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<https://doi.org/10.1016/j.ssmph.2021.100989>

Received 14 April 2021; Received in revised form 17 November 2021; Accepted 30 November 2021

Available online 4 December 2021

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deleterious effects of sedentary occupations exhibit subtle differences between prolonged and interrupted patterns (Diaz et al., 2017; Leitzmann et al., 2018). The unsettled relationship between occupation-based PA and health outcomes underscores the need to revisit the association between occupation and PA in the first place, which can be facilitated by objective measures of PA in frequency, intensity, and duration.

This study sets out to accomplish a better understanding of occupational determinant of PA at work using accelerometry data. It not only addresses limitations of previous work of self-report and invalidity of PA during nonworking hours, but also sheds light on PA accumulation pattern in addition to its total volume. Capitalizing on US nationally representative data from 2005 to 2006 National Health and Nutrition Examination Survey (NHANES), we provide evidence for PA volume and fragmentation among broad occupational groups and reveal how occupations may accumulate the same volume of activity differently. We also identify the contribution of occupational difference relative to the contribution of workers' attributes. The established occupation-PA link sets the stage for unpacking the occupation-health black box in future studies and helps design effective policies for workers' health promotion.

## 2. Occupation as a social determinant of PA

Occupation determines PA at work, which operates independently of the socioeconomic aspects of occupations (Burgard & Lin, 2013; Toch et al., 2014). While leisure-time PA usually involves conscious planning, self-controlled time and sufficient recovery, occupation-based PA is primarily determined by occupational tasks beyond workers' control (Holtermann et al., 2018; Hadgraft et al., 2018). Existing studies on work conditions have shed light on the psychosocial conditions of occupation and its influences on leisure-time PA (e.g., different job stressors and job stress from imbalanced demand/control, see Mutz et al., 2020; Abdel Hadi et al., 2021). Less attention is paid to the physical conditions that are equally important (Toch et al., 2014; Grzywacz et al., 2016). While exposures to physical/chemical hazards have been reduced with the transition to service-oriented economy and the introduction of health and safety legislations, repetitive motion and prolonged sedentary behaviors are increasingly relevant in post-industrial societies, especially in production, service, and professional occupations (Burgard & Lin, 2013; Torch et al., 2014).

Building on social stratification theory (Weeden & Grusky, 2012) and the ecological model of health behavior (Hadgraft et al., 2018), we maintain that occupation determines the frequency, intensity, and duration of physical movement during working hours through the stipulated tasks. The standard occupational classification (SOC, Bureau of Labor Statistics) has been updated and aligned with the Occupational Information Network (O\*NET),<sup>1</sup> which specifies the physical abilities required to perform that occupation, as well as the time and repetitiveness of those physical actions. For example, computer scientists and engineers may engage in long periods of continuous sedentary behaviors while programming. Teachers and healthcare practitioners move frequently to perform teaching and caregiving tasks, respectively. For service-related occupations, the typical activities involved in food preparation differ from those assisting with personal hygiene and service.

Self-reported measures, however, are unable to meaningfully differentiate PA between occupations that involve a combination of sedentary behaviors (e.g., sitting) and periods of low- or light-intensity activities (e.g., walking) even when recalls are reasonably accurate (Ainsworth et al., 1999; Maes et al., 2020). For example, Tudor-Locke et al. (2011) develop a set of activity codes to estimate the energy expenditure for 22 major occupational groups. These activity codes

represent 16 combinations of body position (sit, walk, stand, and heavy labor) and intensity levels (low, moderate, and high). Each occupation is assigned with a wide range of activity codes based on the authors' independent evaluations and consensus. For example, computer/mathematical and production are both assigned with nine activity codes from "sit, light" to "sit, stand, walk, not carry". Moreover, it is impossible to identify differences in how workers accumulate PA when energy expenditures are similar, which further limits the use of PA variation that bears meaningful implications for health outcomes.

Although accelerometry-based studies have provided unbiased, objective estimates of PA (Steeves et al., 2018; Pulakka et al., 2018; Quinn et al., 2020), these studies usually examine overall daily volume of PA by occupational classification, which fail to separate occupation-based PA from leisure-time and housework PA. In addition, these studies exclusively focus on PA volume, which may miss features of how individuals accumulate PA. Indices that measure the way in which sedentary and active time is accumulated may provide additional information compared to traditional measures of activity volume. For example, active to sedentary transition probability (ASTP), one measure of PA fragmentation, was found to be associated with functional performance, physiological capacity, and the risk of mortality (Di et al., 2019; Wanigatunga et al., 2019; Reider et al., 2020). Moreover, clinical studies showed that introducing regular interruptions in sedentary time has health benefits (Mailey et al., 2016; Dempsey et al., 2016), pointing to the importance of breaking sedentary bouts (a fragmentation measure) in addition to total sedentary time (a volume measure).

This study considers both PA volume, total activity counts (with log-transformation), and accumulation (bouts of activities) in the form of fragmentation, which expands the set of features considered in previous studies. Specifically, we use sedentary to active transition probability (SATP), a measure of fragmentation analogous to ASTP, to measure an individual's probability of exiting a sedentary bout. To separate PA at work from leisure hours, we focus on workers with regular daytime schedule and use the 9am-5pm interval on weekdays when workers are at work. Given workers' differences in demographics, health preconditions, and socioeconomic status, we employ the regression decomposition method (Blinder, 1973; Oaxaca, 1973) to estimate the extent to which occupation determines workers' PA.

We have two specific research questions. First, how do occupations determine PA measured by volume and fragmentation among regular daytime workers in the United States? Second, how large a share of PA difference between two occupations is attributable to the occupational difference implicitly through occupational tasks, relative to the contribution of workers' demographics, health preconditions, and socioeconomic status?

## 3. Data and methods

### 3.1. Study population

The NHANES is a cross-sectional, nationally representative survey to assess demographic, dietary, and health-related outcomes across all age groups in the United States. Although more recent accelerometry data from 2011 to 2014 survey of NHANES are available, these later rounds did not ask the key question on work schedule, which makes it impossible to differentiate PA between working and nonworking hours. The 2005–2006 survey of NHANES better suits the purpose of this study, for its work schedule information among working adults 16 years old and above.

*Accelerometry data.* The accelerometry data collected by the 2005–2006 NHANES used ActiGraph AM-7164, which is a hip-worn uniaxial device that detects and records the magnitude of acceleration counts of movement at the minute level. It aims to capture the intensity and duration of locomotion activities such as walking and jogging, and the lack of them. In other words, it only measures the intensity and duration of ambulation and differentiates activity from non-activity.

<sup>1</sup> O\*NET OnLine [www.onetonline.org](http://www.onetonline.org).

Because this accelerometer captures moves related to walking and similar types of activity, it does not record upper body movement or differentiate postural changes between sitting and standing. We note this limitation in the Discussion. The description of the 2005–2006 NHANES accelerometry data, as well as the data processing and analytic pipeline used in this study, can be found in [Leroux et al. \(2019\)](#).

**Work schedule.** Respondents are asked a question of “Which best describes hours worked” for their main job or business in the Occupation Questionnaire. They report their answers as regular daytime schedule, regular evening shift, regular night shift, rotating shift, and another shift. Although it is informative to compare PA between workers with regular daytime and other work schedules in the same occupation, it is impossible to approximate the working time for workers with nonstandard schedules without time diary data. Therefore, we select our analytic sample of regular daytime workers, with the assumption that 9-to-5 on weekdays represent their working hours.<sup>2</sup> This helps us differentiate occupation-based PA from PA in nonworking hours.

**Analytic sample.** Our analytic sample is restricted to individuals aged 16–64 who were working ( $n = 2,805$ ), of whom 1,927 (69%) had a regular daytime schedule. Because workers were not asked to report exactly what hours they were at work, focusing on regular daytime workers helps minimize complications associated with workers having irregular working hours. Existing studies usually define good accelerometry data as individuals with at least 10 hours of estimated wear time per day ([Steeves et al., 2015](#); [Leroux et al., 2019](#)). We follow this practice and impose an additional criterion of having at least 3 weekdays of data with good accelerometry data. This yields 1,439 regular daytime workers with 6,401 person-weekday observations. Each person-weekday observation has 481 min from 9am to 5pm, which amounts to 3,078,881 person-minute observations.<sup>3</sup>

### 3.2. Measures

**TLAC<sub>9am-5pm</sub>.** The total log activity count from 9am to 5pm is one of our two dependent variables. It is a measure of volume which summarizes the total PA during normal working hours. Previous studies suggest that the measure of total activity counts per day avoids the choice of an arbitrary cutoff and captures the summary of PA. Compared to the measure of moderate-to-vigorous PA (MVPA), total activity counts have a stronger association with cardiometabolic biomarkers ([Kim et al., 2013](#); [Wolff-Hughes et al., 2015](#)). The log-transformation of minute-level activity counts measures more strongly low-to-light levels of PA ([Varma et al., 2018](#)), which minimizes the influence of potential physical exercise that some workers may perform during the day. We assess the prevalence of physical exercise during the working hours in our sample by calculating 10-minute MVPA bouts. We find that 86% of

<sup>2</sup> To evaluate this assumption, we conducted two auxiliary analyses (see Supplemental Materials). First, we compared PA volume and fragmentation by work schedule among 3 selected occupational groups (Sales, Service, and Manual), because only these occupational groups have at least 30 participants for each specific work schedule (S3a). We found that compared to regular daytime workers, those with a regular evening schedule exhibit substantially lower values of PA volume and fragmentation, close to the PA patterns among workers in Management and Business. To a lesser extent, workers with “a rotating shift” and “another schedule” also have lower values of PA volume and fragmentation, although it is hard to pinpoint their exact working hours (S3b). Second, within daytime regular workers, we visualized their average minute-level log activity counts from 9am to 5pm between weekday and weekend (S4). It shows very different weekday vs. weekend temporal patterns, and the trends on weekend are more similar across occupational groups than during the weekdays. This further illustrates the importance of considering working hours based on work schedule to measure occupation-based PA.

<sup>3</sup> This is derived by  $481 \times 6401$ . Among the analytic sample respondents, 86% have complete wear time of 481 minutes between 9am and 5pm. We control for the total minutes of wear time in the statistical model.

our respondents have no such bouts.<sup>4</sup> This finding, in combination with our log-transformation of activity counts, suggests that our results are unlikely to be confounded by high-intensity physical exercise.

**SATP<sub>9am-5pm</sub>.** Our second dependent variable is a measure of fragmentation of PA, which is sedentary to active transition probability (SATP<sub>9am-5pm</sub>). We define a minute of accelerometry data as sedentary if that minute has fewer than 100 observed activity counts. We estimate the transition probability between sedentary and active states using the estimator described in [Di et al. \(2019\)](#). Specifically, SATP<sub>9am-5pm</sub> is estimated as the total number of 1 min or longer sedentary bouts, divided by the total minutes spent in the sedentary state. Higher values of SATP<sub>9am-5pm</sub> indicate more interruptions of sedentary behaviors. Previous studies have used average sedentary bout duration as a measure of individual tendency to engage in prolonged periods of sedentary behaviors. The use of SATP as opposed to sedentary bout duration is motivated by the comparative strength of ASTP relative to active bout duration in predicting all-cause mortality ([Leroux et al., 2021](#); [Smirnova et al., 2020](#)). This provides information about how individuals accumulate activity and complements the volume measure of PA.

**Occupational grouping.** The 2005–2006 NHANES uses the 2000 Standard Occupational Classification (SOC) from the Bureau of Labor Statistics to identify 22 major occupation groups (excluding military) among working adults. We collapse the 22 occupations into 10 groups based on career-related fields to ensure group size with at least 30 participants (see Online [Appendix A](#)). The 10 collapsed occupational groups include (1) Science, Technology, Engineering, and Mathematics (STEM), (2) Other professional, (3) Management, (4) Business, (5) Office, (6) Sales, (7) Health, (8) Education, (9) Service, and (10) Manual. The broad occupational groups smooth away within-occupation heterogeneity ([Martin-Caughey, 2021](#)), which we note this data limitation in the Discussion.

**Covariates.** We examine covariates that contribute to workers’ PA at work based on previous findings ([Lohne-Seiler et al., 2014](#); [Beenackers et al., 2012](#); [Mirowsky & Ross, 2015](#)). These include four sets of covariates: (1) demographic characteristics (sex, race/ethnicity, age at examination in years, and marital status), (2) health preconditions (whether general health is good or excellent, and whether one has no bad mental days), (3) socioeconomic status (whether one has a bachelor’s degree or higher, and a continuous measure of income-to-needs ratio topped at 5). We also include (4) full-time working status and total minutes of wear time during 9am–5pm, as our analytic sample includes a majority of full-time workers with varying wear time above the threshold of 10 hours per day.

### 3.3. Analytic strategy

**Descriptive analysis.** Our descriptive analysis aims to provide population patterns of occupation-based PA as well as individual attributes. We weigh the results using the sampling weights at examination, a subsample of the interview sample that corresponds to the set of individuals in the accelerometry portion of this study. We follow the NHANES tutorials for variance estimation, which takes into account complex survey design (e.g., differential weighting, clustering, and stratification) using the subsample indicator for Taylor Series Linearization method. In our descriptive analysis, we first examine the distributions of TLAC<sub>9am-5pm</sub> and SATP<sub>9am-5pm</sub> across 10 occupational groups and select major occupations with 30 or more participants. Second, we compare these two PA measures to seek for additional insights into occupation-based PA. Third, we provide the descriptive statistics of covariate distributions by occupational group and prepare for

<sup>4</sup> We calculate 10-minute moderate-to-vigorous activity bouts (defined as at least 2020 total PA counts) with either a tolerance of 2 minutes below 100 activity counts or 3 minutes below. We found that 86% and 82% of person-weekday observations do not have these bout minutes, respectively.

decomposition analysis.

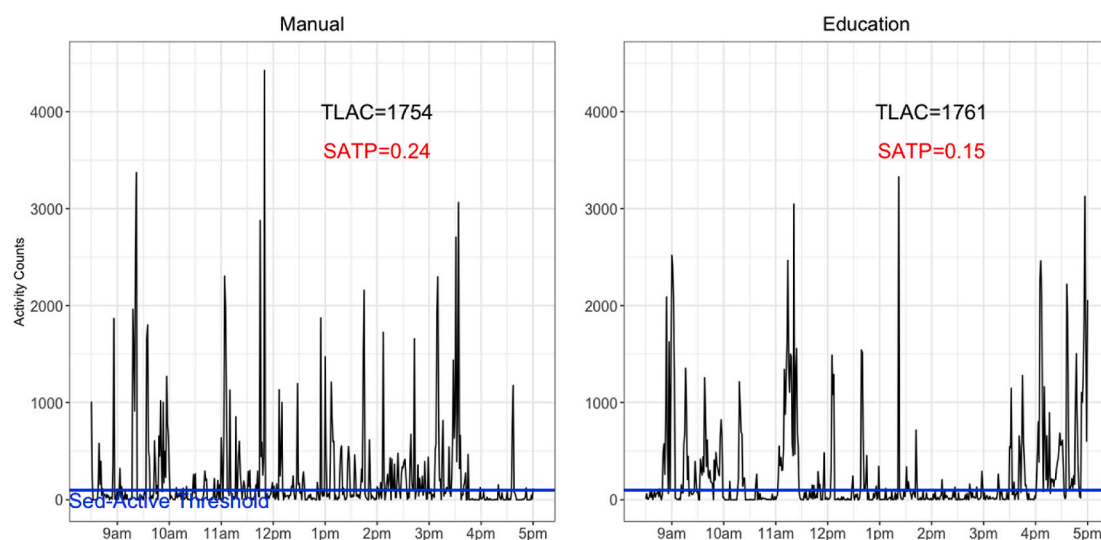
**Regression decomposition.** We apply the updated Blinder-Oaxaca regression decomposition to our analysis (Blinder, 1973; Oaxaca, 1973; Yun 2005a, 2005b). The regression decomposition analysis is weighted using the 2-year examination weights for population inference. For any pair of occupations, we decompose the expected difference in PA into two contributions: (1) the compositional contribution capturing the difference in the distribution of the covariates, and (2) the coefficient contribution capturing the difference in the coefficients for the covariates between the two occupations being compared (see Online Appendix B). For each of a total  $(10 \times 9)/2 = 45$  possible pairs from 10 occupational groups, we regress  $TLAC_{9am-5pm}$  or  $SATP_{9am-5pm}$  on the covariates. We visualize decomposition results for 45 pairs of occupations and present selected results in tables to highlight substantive findings. We use the *rnhanesdata* package in R (Leroux et al., 2019) to process accelerometry data, construct PA variables, and create graphs for visualization. Descriptive and decomposition analyses (“oaxaca-”) are performed using STATA 16.

## 4. Results

### 4.1. Accelerometry PA across occupation groups

Fig. 1 illustrates the fragmentation measure, or sedentary-to-active transition probability ( $SATP_{9am-5pm}$ ), which reveals how activity is accumulated differently with a fixed volume of PA ( $TLAC_{9am-5pm}$ ). It presents the daily activity counts between 9am and 5pm for two individuals holding a Manual occupation and an Education occupation. They have similar levels of  $TLAC_{9am-5pm}$  (1754 and 1761) but different  $SATP_{9am-5pm}$  (0.24 vs. 0.15). Specifically, the Manual worker (left panel) has fewer numbers of sedentary bouts, roughly indicated by more frequent spikes above the blue line corresponding to the threshold for sedentary behaviors (100 activity counts). This difference is especially apparent between 2pm and 4pm, where the Education worker (right panel) is inactive for nearly the entire period. This demonstrates the additional information gained by considering fragmentation in addition to the volume of PA, which reveals how workers accumulate the same PA volume: frequent interruptions versus prolonged sedentary behaviors.

Table 1 presents the means and standard deviations (in parentheses)



**Fig. 1.**  $SATP_{9am-5pm}$  between Two Individuals with Similar Levels of  $TLAC_{9am-5pm}$ . Notes: This plot uses two individual profiles to illustrate PA differences using fragmentation measure ( $SATP_{9am-5pm}$ ) with similar total volumes ( $TLAC_{9am-5pm}$ ). Individual 1 holds a Manual occupation and Individual 2 holds an Education occupation. The blue line indicates the threshold between sedentary and active intensity at 100 activity counts. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Source: 2005–2006 National Health and Nutrition Examination Survey.

of accelerometry volume ( $TLAC_{9am-5pm}$ , in ascending order) and fragmentation measure ( $SATP_{9am-5pm}$ ) across 10 occupational groups and selected major occupations, regardless of their full- or part-time status (see Supplemental Materials S1 for the distribution of PA outcomes among full-time workers).

Table 1 gives rise to three patterns. First, the means of  $SATP_{9am-5pm}$  rank largely the same as those of  $TLAC_{9am-5pm}$ , suggesting a positive correlation between the volume measure and the fragmentation measure (Pearson correlation of 0.86, ranging from 0.79 among Service and 0.89 among STEM, results not shown). Second, when the average of volume or fragmentation is lower, the dispersion is also smaller with one exception: the Sales group exhibits a lower mean and a higher SD in both volume and fragmentation measures. This suggests that some Sales workers have very light while other have quite high occupation-based PA. Third, there is also heterogeneity within occupational groups such as STEM and Service. For example, STEM workers in Computer, mathematical occupation have particularly low levels of PA compared to Architecture, engineering ( $TLAC_{9am-5pm}$  of 1146 vs. 1407). In contrast, Service workers in Food preparation serving (2080) and Building/grounds maintenance (2180) have an average PA volume resembling those in Manual occupations (2130). Moreover, they exhibit the widest distribution (SD of 638 for Food and 535 for Building), suggesting that their occupational tasks vary greatly in physical movements. We will examine how this pattern holds up in regression analysis.

### 4.2. Visualization of accelerometry PA at the minute level

To assess any temporal differences in activity accumulation which might not be apparent in day-level averages, Fig. 2 presents the minute-level difference in log activity count (LAC) between 9am and 5pm for four selected pairs of occupational groups. We present the weighted means for each pair of occupations (two grey lines), the weighted occupational differences in LAC by time of day (bolded black line), and the smoothed occupational difference using 30-minute rolling average (colored).

Of the occupations shown in Fig. 2, Manual and STEM occupations (subplot A) represent the two extremes in occupation-based PA, with a wide gap in minute-level log activity counts (LAC) above 2. Additionally, there is a temporal pattern to the difference, which is relatively constant from 9am to 3:30pm with two exceptions. First, there is a dip in



**Table 1**

Weighted mean (SD) of accelerometry volume (TLAC<sub>9am-5pm</sub>) and fragmentation (SATP<sub>9am-5pm</sub>) across occupational groups and selected major occupations.

| Occupational Group (major occupation) | TLAC <sub>9am-5pm</sub> (SD) | SATP <sub>9am-5pm</sub> (SD) | Sample n | Weighted n |
|---------------------------------------|------------------------------|------------------------------|----------|------------|
| 1. STEM                               | 1307 (343)                   | 0.15 (0.06)                  | 84       | 100        |
| Computer, mathematical                | 1146 (303)                   | 0.12 (0.05)                  | 32       | 35         |
| Architecture, engineering             | 1407 (346)                   | 0.17 (0.06)                  | 34       | 47         |
| 2. Other professional                 | 1464 (308)                   | 0.17 (0.05)                  | 52       | 55         |
| 3. Management                         | 1550 (297)                   | 0.18 (0.06)                  | 119      | 164        |
| 4. Business, financial operations     | 1541 (351)                   | 0.19 (0.07)                  | 70       | 71         |
| 5. Office, administrative support     | 1682 (358)                   | 0.22 (0.08)                  | 227      | 228        |
| 6. Sales                              | 1736 (410)                   | 0.23 (0.09)                  | 103      | 105        |
| 7. Health                             | 1739 (325)                   | 0.24 (0.07)                  | 99       | 117        |
| Healthcare practitioner, technical    | 1707 (291)                   | 0.23 (0.06)                  | 59       | 83         |
| Healthcare support                    | 1817 (398)                   | 0.26 (0.08)                  | 40       | 34         |
| 8. Education, training, library       | 1806 (315)                   | 0.23 (0.06)                  | 81       | 102        |
| 9. Service                            | 2000 (544)                   | 0.25 (0.11)                  | 176      | 127        |
| Personal care, service                | 1931 (474)                   | 0.26 (0.10)                  | 37       | 30         |
| Food preparation serving              | 2080 (638)                   | 0.29 (0.15)                  | 51       | 24         |
| Building/grounds maintenance          | 2180 (535)                   | 0.26 (0.11)                  | 62       | 29         |
| 10. Manual                            | 2130 (466)                   | 0.29 (0.11)                  | 428      | 370        |
| Installation, maintenance, repair     | 2051 (407)                   | 0.29 (0.10)                  | 51       | 60         |
| Production                            | 2101 (488)                   | 0.28 (0.11)                  | 114      | 89         |
| Transportation, material moving       | 2106 (447)                   | 0.29 (0.11)                  | 108      | 84         |
| Construction, extraction              | 2221 (490)                   | 0.31 (0.11)                  | 147      | 130        |

Notes: The selected occupations have at least 30 participants with tracked accelerometry measures from the 22 occupational classifications in 2005–2006 NHANES. See Online Appendix A for a complete list of occupations under each group. Standard deviations are in parentheses. Statistics are weighed with 2-year weights at examination. The calculation of variance estimates follows the guidance from NHANES CDC tutorial (<https://www.cdc.gov/nchs/nhanes/tutorials/module4.aspx>).

Source: 2005–2006 National Health and Nutrition Examination Survey.

the average activity among Manual workers around 12:00pm-12:30pm, possibly corresponding to a lunch break period. Second, Manual workers' average PA decreases around 4pm when STEM workers average PA increases, causing the difference between the two occupations to shrink markedly. Compared to self-reported measures that are unable to consider periods of occupational tasks with low PA (Dayaert et al., 2017), this underscores the utility of accelerometers that captures minute-level differences. Second, in the comparison between Service and Health workers (subplot B), the difference in minute-level PA lies within [0.5, 1] LAC before 4pm, after which time the difference shrinks to zero by 5pm.

While the activity difference between Service and Health workers is not as large as that observed between Manual and STEM workers, it demonstrates that Health workers, on average, accumulate lower PA at a near constant rate as compared to Service workers during work hours. Third, we note the similarities in PA comparing Office and Management (subplot C), and Manual and Service workers (subplot D), with average differences roughly between 0 and 0.5 LAC for the majority of working time. For these two occupations, PA using SATP<sub>9am-5pm</sub> measure provides fragmentation difference and reflects occupational task differences (Office vs. Management: 0.22 vs. 0.18, p-value<.001; Manual vs. Service: 0.29 vs. 0.25, p-value<.001). In general, the weighted mean

difference between paired occupations is relatively stable between 9am and 5pm, suggesting that our global summaries of volume do not lose much information about occupational differences in average PA.

#### 4.3. Differences in covariates across occupational groups

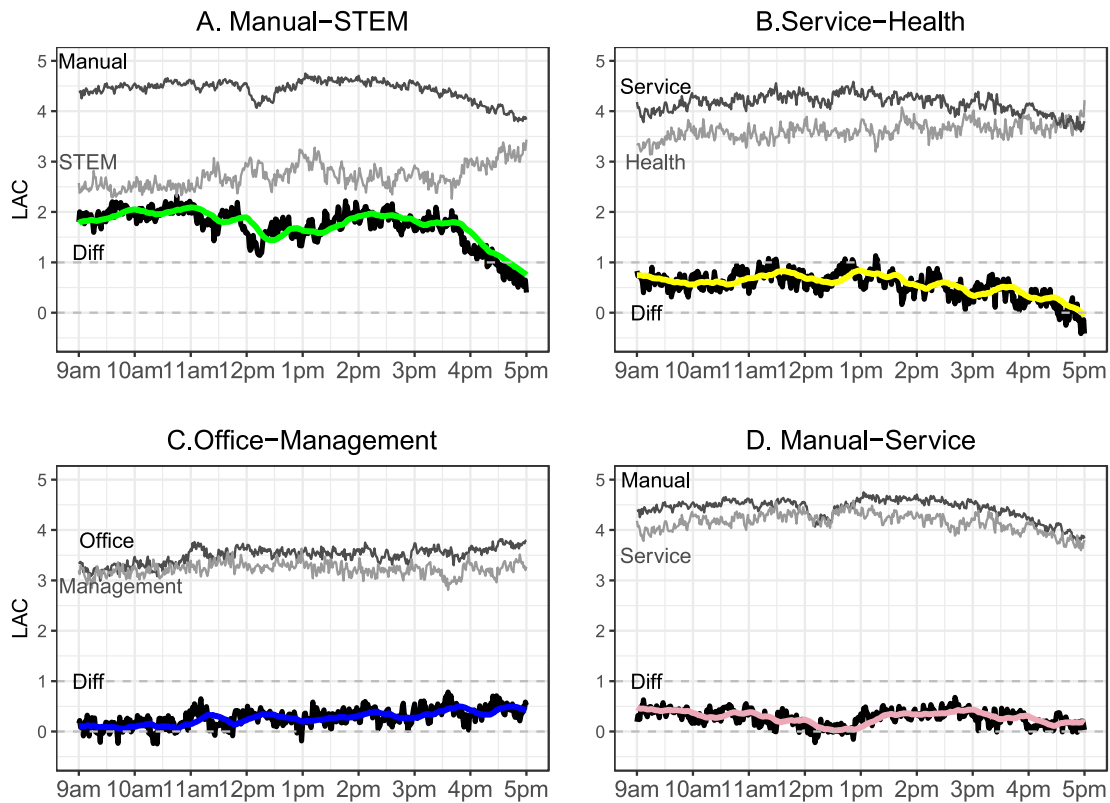
Our descriptive analysis and visualization demonstrate the differentiation of occupation-based PA summarized at both day and minute resolutions. However, observed occupational differences may be partially explained by the compositional differences of workers in demographics, health preconditions, and socioeconomic status. Table 2 presents the distribution of these predictors across occupations. Consistent with the literature on occupational segregation by demographic characteristics (Blau et al., 2013; del Río & Alonso-Villar, 2015), it shows that certain occupations are highly segregated along gender and race/ethnicity lines. For example, STEM and Manual occupations are male-dominated (0.28 and 0.14 female proportion, respectively), while Health (0.83), Office (0.79), and Education (0.76) occupations are female-dominated. Moreover, racial minority workers are more likely to concentrate in Service and Manual occupations. Aside from demographic compositional differences, workers in professional occupations (e.g., STEM, Management, Business, and Education) are also more likely to hold a bachelor's degree and have higher income-to-needs ratio than workers in other occupations.

#### 4.4. Decomposition for pairwise occupational groups

To demonstrate the advantages of regression decomposition over ordinary regression models, we regress our two outcome variables on occupational dummies and the set of covariates, respectively (see Supplemental Materials S2). The general occupational patterns of both TLAC<sub>9am-5pm</sub> or SATP<sub>9am-5pm</sub> are consistent with the descriptive results, with the largest observed difference between Manual and STEM workers. However, the ordinary regression results only show us how much the PA variation is explained by occupation, net of compositional differences. In other words, the ordinary regression cannot tell us how large a share of the difference between two occupational groups is contributed by occupational effects relative to workers' compositional differences.

We now turn to the decomposition results using the comparison between Manual and STEM in TLAC<sub>9am-5pm</sub> as an illustration. According to the top panel of Table 3, the predicted means of TLAC<sub>9am-5pm</sub> for Manual and STEM workers are 2130 and 1307, respectively. Of a difference of 823 on average, 82% is contributed by coefficient differences due to occupations, while 18% contributed by the compositional differences in predictors such as demographics, health preconditions, and socioeconomic status. The bottom panel in Table 3 presents information on the compositional differences and coefficient differences associated with each covariate. We are particularly interested in the coefficient differences that either have opposite signs or substantial difference in magnitude. For example, although both Manual and STEM occupations are overrepresented by male workers (0.28 and 0.14 proportion female, respectively), female is less physically active than male in Manual occupations but more active than male in STEM occupations (regression coefficients of -154.4 and 139.6, respectively). This dramatic difference in coefficients reflects how these two occupations affect women's PA differently. In total, the differential occupational effect by sex suppresses the total difference by -10.8%<sup>5</sup> (the last column), implying that Manual occupations would have higher PA volume than STEM occupations if female workers were to be more physically active than male in Manual occupations as their female counterparts in STEM occupations. Similarly, although only 6% of Manual workers hold a bachelor's degree or

<sup>5</sup> This is calculated as  $-72.7/673.7$ , which is the female coefficient/total coefficient difference, results not shown.



**Fig. 2.** Levels of and Differences in Minute-Level Log Activity Counts between Pairs of Occupations

Notes:  
 The figures visualize the weighted log activity counts for 4 pairs of occupations, their weighted mean difference (bolded black line), and its smoothed curve (30-minute rolling average, colored) from 9am to 5pm among daytime regular workers. These pairwise comparisons reflect interests in A. Occupations with TLAC<sub>9am-5pm</sub> at two extremes; B. Moderate differences between Health and Service; C. Occupations are similarly sedentary; and D. Occupations are similarly active.  
 Source: 2005–2006 National Health and Nutrition Examination Survey.

**Table 2**  
 Descriptive statistics of covariates by occupational groups.

|                            | STEM  | Other prof | Management | Business | Office | Sales | Health | Education | Service | Manual |
|----------------------------|-------|------------|------------|----------|--------|-------|--------|-----------|---------|--------|
| <b>Demographic</b>         |       |            |            |          |        |       |        |           |         |        |
| Female                     | 0.28  | 0.70       | 0.44       | 0.67     | 0.79   | 0.46  | 0.83   | 0.76      | 0.53    | 0.14   |
| <b>Race/ethnicity</b>      |       |            |            |          |        |       |        |           |         |        |
| White                      | 0.80  | 0.77       | 0.89       | 0.65     | 0.69   | 0.80  | 0.76   | 0.89      | 0.57    | 0.67   |
| Black                      | 0.09  | 0.11       | 0.04       | 0.17     | 0.12   | 0.07  | 0.12   | 0.05      | 0.14    | 0.08   |
| Hispanic                   | 0.04  | 0.09       | 0.02       | 0.09     | 0.12   | 0.08  | 0.05   | 0.02      | 0.23    | 0.21   |
| Other                      | 0.08  | 0.03       | 0.04       | 0.09     | 0.07   | 0.05  | 0.07   | 0.04      | 0.05    | 0.03   |
| Age at examination         | 41.7  | 43.1       | 45.3       | 40.4     | 41.6   | 44.2  | 43.6   | 44.5      | 42.9    | 42.5   |
| Married                    | 0.74  | 0.69       | 0.84       | 0.65     | 0.65   | 0.79  | 0.71   | 0.83      | 0.67    | 0.76   |
| <b>Health precondition</b> |       |            |            |          |        |       |        |           |         |        |
| General                    | 0.91  | 0.86       | 0.88       | 0.91     | 0.86   | 0.89  | 0.88   | 0.95      | 0.85    | 0.80   |
| Mental                     | 0.67  | 0.53       | 0.62       | 0.53     | 0.54   | 0.55  | 0.69   | 0.57      | 0.60    | 0.64   |
| <b>Socioeconomic</b>       |       |            |            |          |        |       |        |           |         |        |
| BA or higher               | 0.60  | 0.60       | 0.54       | 0.53     | 0.20   | 0.32  | 0.42   | 0.83      | 0.11    | 0.06   |
| Income-to-needs ratio      | 4.2   | 4.0        | 4.3        | 4.0      | 3.4    | 3.7   | 3.9    | 3.9       | 2.4     | 2.9    |
| Full-time                  | 0.90  | 0.79       | 0.93       | 0.87     | 0.84   | 0.90  | 0.73   | 0.73      | 0.70    | 0.84   |
| Total wear minutes         | 466.6 | 472.7      | 475.6      | 473.4    | 471.9  | 466.2 | 461.0  | 469.9     | 463.9   | 469.1  |
| N                          | 84    | 52         | 119        | 70       | 227    | 103   | 99     | 81        | 176     | 428    |
| Person-weekday obs.        | 382   | 222        | 551        | 309      | 1016   | 453   | 431    | 367       | 760     | 1910   |

Notes:  
 The statistics are weighed using 2-year examination weights.  
 Source: 2005–2006 National Health and Nutrition Examination Survey.

higher, the negative association between of BA and TLAC<sub>9am-5pm</sub> is smaller for Manual workers (−101.9, p-value = .099) than for STEM workers (−161.9, p-value = .002). Again, occupations assign college-

educated STEM workers with fewer labor-intensive tasks as compared to Manual workers.

Moving to the complete set of 45 occupational pairs, we visualize the

**Table 3**  
Detailed regression decomposition results of occupation contribution to accelerometry volume (TLAC<sub>9am-5pm</sub>) of manual and STEM occupations.

|                          |             |       |               |                              |                             |                      | TLAC <sub>9am-5pm</sub> |
|--------------------------|-------------|-------|---------------|------------------------------|-----------------------------|----------------------|-------------------------|
| Manual                   |             |       |               |                              |                             |                      | 2130                    |
| STEM                     |             |       |               |                              |                             |                      | 1307                    |
| Expected mean difference |             |       |               |                              |                             |                      | 823                     |
| Contribution             |             |       |               |                              |                             |                      |                         |
| Due to coefficients (%)  |             |       |               |                              |                             |                      | 674 (82%)               |
| Due to composition (%)   |             |       |               |                              |                             |                      | 149 (18%)               |
| Covariate                | Composition |       |               | Coefficient                  |                             | Relative coefficient |                         |
|                          | Manual      | STEM  | Diff: p-value | Manual                       | STEM                        | Contribution (%)     | p-value                 |
| Female                   | 0.14        | 0.28  | 0.000         | -154.4<br>[-225.52, -83.23]  | 139.6<br>[44.47, 234.76]    | -10.8                | 0.000                   |
| Black                    | 0.08        | 0.09  | 0.778         | -55.7<br>[-121.36, 9.93]     | -21.0<br>[-135.24, 93.22]   | -0.4                 | 0.605                   |
| Hispanic                 | 0.22        | 0.04  | 0.000         | 13.6<br>[-47.48, 74.76]      | 232.4<br>[39.50, 425.27]    | -2.2                 | 0.013                   |
| Other                    | 0.04        | 0.08  | 0.000         | -204.4<br>[-361.03, -47.81]  | -191.4<br>[-368.32, -14.39] | 0.0                  | 0.994                   |
| Age at examination       | 41.9        | 41.7  | 0.658         | -4.6<br>[-6.64, 2.51]        | 6.6<br>[2.30, 10.85]        | -69.1                | 0.000                   |
| Married                  | 0.75        | 0.74  | 0.660         | 9.1<br>[-53.49, 71.74]       | 107.6<br>[-7.87, 223.14]    | -10.8                | 0.142                   |
| Good or very good        | 0.80        | 0.91  | 0.000         | 13.7<br>[-55.99, 83.38]      | 90.3<br>[-27.79, 208.42]    | -10.0                | 0.285                   |
| No bad mental days       | 0.64        | 0.67  | 0.167         | -4.1<br>[-54.97, 46.72]      | -138.8<br>[-256.62, -20.93] | 13.4                 | 0.039                   |
| BA/+                     | 0.06        | 0.60  | 0.000         | -101.9<br>[-222.99, 19.22]   | -161.9<br>[-265.32, -58.44] | 2.6                  | 0.484                   |
| Income-to-needs ratio    | 2.85        | 4.17  | 0.000         | -37.7<br>[-59.21, -16.28]    | -54.6<br>[-101.18, -8.06]   | 10.5                 | 0.494                   |
| Full-time status         | 0.83        | 0.90  | 0.000         | 135.5<br>[-65.83, 205.10]    | 177.6<br>[47.57, 307.62]    | -5.8                 | 0.560                   |
| Total wear minutes       | 468.8       | 466.5 | 0.348         | 5.8<br>[5.33, 6.36]          | 2.2<br>[1.64, 2.76]         | 252.9                | 0.000                   |
| Constant                 | -           | -     | -             | -403.8<br>[-665.51, -142.16] | 70.9<br>[-342.08, 483.88]   | -70.5                | 0.057                   |
| R-squared                | -           | -     | -             | 0.30                         | 0.24                        | -                    | -                       |

Notes: The top panel summarizes the regression decomposition results and the bottom panel presents the detailed estimates. 2-year examination weights are applied for population inference. The “Composition” column shows the covariate compositions for the two occupations, with the p-values for their differences. The “Coefficient” column presents the regression coefficients of the covariates for Manual and STEM occupational groups, respectively. 95% confidence intervals are in brackets. The “Relative Coefficient Contribution” column tells the relative share of the coefficient of covariates (sum to 100.0%), which is ratio of the covariate coefficient to total coefficient differences. Source: 2005–2006 National Health and Nutrition Examination Survey.

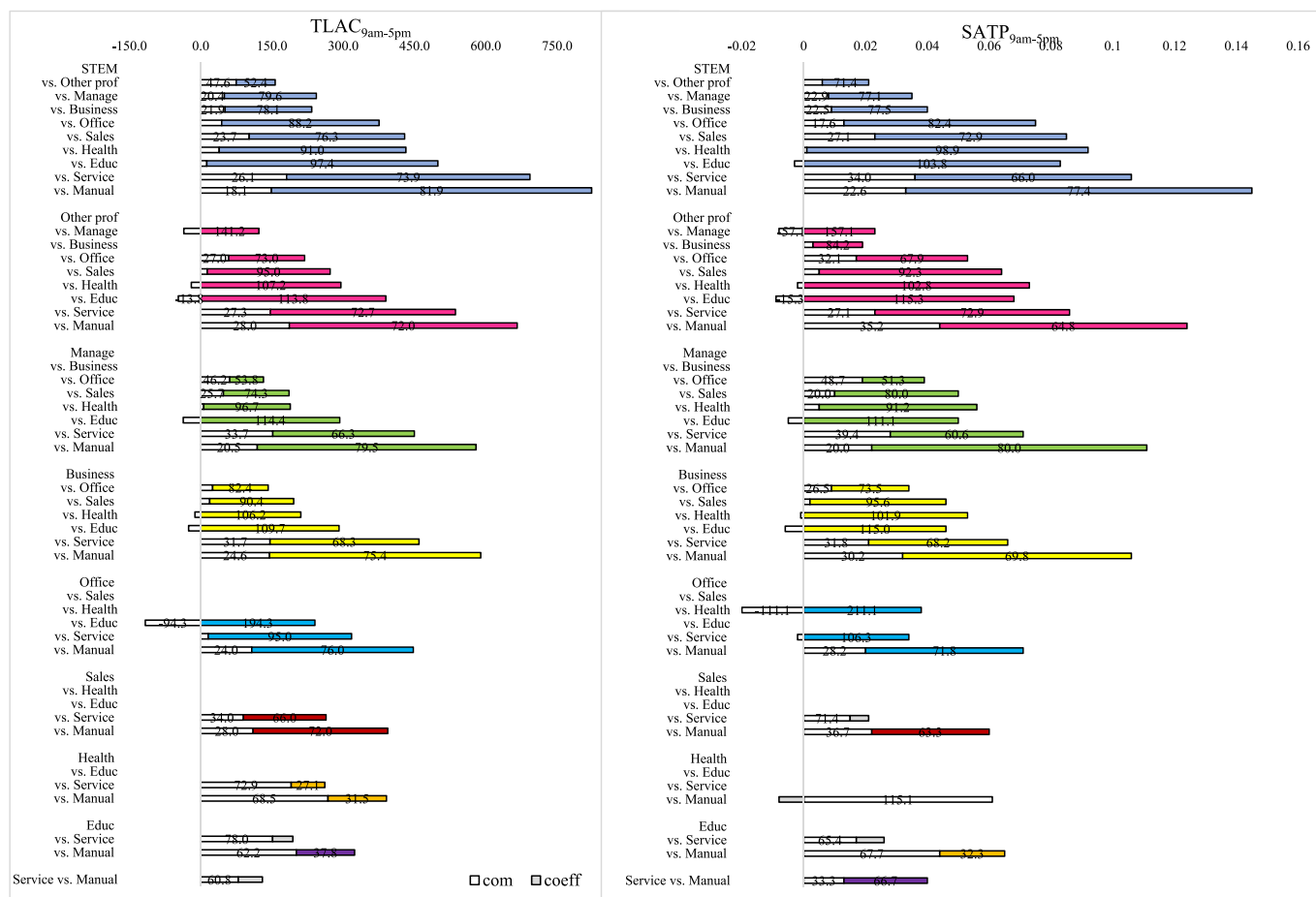
decomposition results with significant PA difference in Fig. 3. We identify four major patterns and illustrate each pattern with a concrete example in Table 4. First, occupations contribute to a substantial share of the total PA difference relative to the compositional distribution of covariates, especially when two occupations differ in educational requirements. This is evidenced by the comparisons including STEM vs. Manual, STEM vs. Service, Business vs. Service, Sales vs. Manual, and Management vs. Service in Fig. 3. For example, according to the top panel of Table 4, Manual and STEM differ substantially in workers with a bachelor’s degree or higher (0.06 for Manual, 0.60 for STEM). Occupations contribute to 82% (TLAC<sub>9am-5pm</sub>) and 77% (SATP<sub>9am-5pm</sub>) of the total difference. The effects of occupations can be further indicated by the largest relative share from the coefficient of wear time: 252.9% in TLAC<sub>9am-5pm</sub> and 318.8% in SATP<sub>9am-5pm</sub>, where the positive association between wear time and PA is stronger for Manual than STEM (5.8 vs. 2.2 in TLAC<sub>9am-5pm</sub>). Given that Manual and STEM workers do not differ in total wear time (468.8 vs. 466.5, p-value = .35), it further implies that it is the occupational tasks that drive the PA difference at work.

Second, when two occupations further vary in demographic characteristics in addition to educational requirements, more of the PA difference can be explained by their compositional covariates. For example, the comparison between Manual and Education (second panel in Table 4) shows 62% (TLAC<sub>9am-5pm</sub>) and 68% (SATP<sub>9am-5pm</sub>) are explained by compositional differences. Compared to 18% (TLAC<sub>9am-5pm</sub>) and 23% (SATP<sub>9am-5pm</sub>) compositional contributions in

Manual vs. STEM comparison, Education further differs from Manual in greater female concentration (0.76 vs. 0.14 female proportion), where female effect suppresses the difference by 63.2% and 145.8% in TLAC<sub>9am-5pm</sub> and SATP<sub>9am-5pm</sub>, respectively. Similar patterns can be found in the comparisons such as Management vs. Office, Health vs. Manual, and Education vs. Service in Fig. 3, where these occupations differ in both educational requirements and demographic characteristics.

Third, when occupations are similar in educational requirements, it may further depend on whether they require higher educational levels or not. For example, within occupations that require higher educational levels, such as Health vs. STEM (the third panel of Table 4, 0.42 vs. 0.60 BA or higher), 91% (TLAC<sub>9am-5pm</sub>) and 99% (SATP<sub>9am-5pm</sub>) of PA difference is due to occupational coefficients, although they differ vastly in female concentration compositions (0.83 vs. 0.28). Similar patterns can be found in the comparisons such as STEM vs. Manage, STEM vs. Business, Manage vs. Education, and Manage vs. Health. For these comparisons, all share above 70% of coefficient contribution, despite of demographic compositional differences. This may imply that professional occupations may involve specialized skills and detailed tasks that shape PA differently at work. In contrast, for two occupations with low educational requirement, such as Manual vs. Service, 61% difference in PA volume can be explained by their compositional differences (bottom panel of Table 4).

Fourth, SATP<sub>9am-5pm</sub> may identify substantial contributions by occupations not found in TLAC<sub>9am-5pm</sub>. This is indicated by the comparisons between Manual vs. Service, Office vs. Health, and Other



**Fig. 3.** Significant Occupational Contribution (% in Color) to the PA Difference of each of the 45 Occupation Pairs. Notes: only paired occupations with substantial difference in either TLAC<sub>9am-5pm</sub> or SATP<sub>9am-5pm</sub> are presented. The percentage contribution is shown for decomposition components that are statistically significant. Specifically, the bar for contribution due to compositional difference is white, which indicates PA difference due to compositional difference in workers’ demographic, pre-health conditions, socioeconomic attributes. The bar for contribution due to coefficient difference is colored, which indicates difference due to coefficients or occupational effects.  
 Source: 2005–2006 National Survey of Health and Nutrition Examination Survey. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

professional vs. Business in Fig. 3. Take the comparison between Manual vs. Service for example, we find that 67% in SATP<sub>9am-5pm</sub> is due to occupational coefficient (p-value<.001), relative to 39% in TLAC<sub>9am-5pm</sub> (p-value = .067). Details of decomposition (results not shown) suggest that female workers are associated with lower TLAC<sub>9am-5pm</sub> in both occupations. However, female workers have a negative association with sedentary-to-active transition probability (−0.042, p-value<.001) in Manual occupations but a positive association in Service occupations (0.021, p-value = .059). This indicates that female workers may take more sedentary breaks to perform tasks than men in Service occupations but not in Manual occupations, although they accumulated lower volume of PA than men in both occupations. In other words, occupations further shape how PA is accumulated.

**5. Discussions**

Occupational tasks have undergone rapid changes and reshaped how PA is performed (Brownson et al., 2005; Ruggie 2015; Martinez, 2019; Green, 2012). Meanwhile, irregular work schedules have become commonplace (Gerstel & Clawson, 2018; Schneider & Harknett, 2019). Understanding the occupational determinants of workers’ PA at work is the first, straightforward step to track those macro changes on workers’ health behaviors, which in turn help design effective policy interventions for population health.

The rapid adoption of wearable technology among the general population and in large-scale, nationally representative surveys opens opportunities for objectively monitoring PA among workers. This has advanced scientific investigation into the occupation-PA relationship beyond using self-reported measures. Nevertheless, the lack of work schedule data in national surveys has limited researchers’ ability to measure occupation-based PA. A scientific investigation entails a rigorous design that utilizes accelerometry PA and the observation of PA during working hours to separate out leisure-time PA. Moreover, PA fragmentation provides nuanced implications for health beyond volume measure. This study has addressed the common shortcomings of previous studies using either self-reported PA or using accelerometry data without considering the work schedule and PA fragmentation.

While confirming previously published results about manual and STEM occupations occupying the two extremes of the movement spectrum (Steeves et al., 2018), our findings go far beyond the existing literature. First, we discover that workers in education and health occupations are also physically active, suggesting the oversimplification of the dichotomous white-collar and blue-collar occupational groups (Beenackers et al., 2012; Kirk & Rhodes, 2011). Second, we reveal that even when workers accumulate a similar volume of PA at work (e.g., office vs. management, and manual vs. service), PA fragmentation (SATP<sub>9am-5pm</sub>) differs in the ways how the same volume of activity is accumulated.



**Table 4**  
Regression decomposition results of occupation contribution to accelerometry volume (TLAC<sub>9am-5pm</sub>) and fragmentation (SATP<sub>9am-5pm</sub>) of selected pairs.

|                                       | TLAC <sub>9am-5pm</sub> | p-value | SATP <sub>9am-5pm</sub> | p-value |
|---------------------------------------|-------------------------|---------|-------------------------|---------|
| <b>1. Manual-STEM</b>                 |                         |         |                         |         |
| Expected difference                   | 823                     | 0.000   | 0.145                   | 0.000   |
| Decomposition                         |                         |         |                         |         |
| Due to coefficients (%)               | 674 (82%)               | 0.000   | 0.112 (77%)             | 0.000   |
| Due to composition (%)                | 149 (18%)               | 0.000   | 0.033 (23%)             | 0.000   |
| Relative coefficient contribution (%) |                         |         |                         |         |
| Female                                | -10.8                   | 0.000   | -10.2                   | 0.000   |
| Age at examination                    | -69.1                   | 0.000   | -47.8                   | 0.011   |
| Wear time                             | 252.9                   | 0.000   | 318.8                   | 0.000   |
| <b>2. Manual-Education</b>            |                         |         |                         |         |
| Expected difference                   | 324                     | 0.000   | 0.065                   | 0.000   |
| Decomposition                         |                         |         |                         |         |
| Due to coefficients (%)               | 123 (38%)               | 0.009   | 0.021 (32%)             | 0.049   |
| Due to composition (%)                | 201 (62%)               | 0.000   | 0.044 (68%)             | 0.000   |
| Relative coefficient contribution (%) |                         |         |                         |         |
| Female                                | -63.2                   | 0.037   | -145.8                  | 0.000   |
| Age at examination                    | -224.3                  | 0.004   | -164.2                  | 0.079   |
| Income-to-needs ratio                 | -131.6                  | 0.027   | -107.2                  | 0.161   |
| <b>3. Health-STEM</b>                 |                         |         |                         |         |
| Expected difference                   | 432                     | 0.000   | 0.092                   | 0.000   |
| Decomposition                         |                         |         |                         |         |
| Due to coefficients (%)               | 393 (91%)               | 0.000   | 0.091 (99%)             | 0.000   |
| Due to composition (%)                | 39 (9%)                 | 0.165   | 0.001 (1%)              | 0.857   |
| Relative coefficient contribution (%) |                         |         |                         |         |
| Female                                | -28.1                   | 0.011   | -9.4                    | 0.371   |
| Hispanic                              | -4.1                    | 0.002   | -2.9                    | 0.014   |
| Wear time                             | 206.3                   | 0.000   | 169.2                   | 0.000   |
| <b>4. Manual-Service</b>              |                         |         |                         |         |
| Expected difference                   | 130                     | 0.000   | 0.039                   | 0.000   |
| Decomposition                         |                         |         |                         |         |
| Due to coefficients (%)               | 51 (39%)                | 0.067   | 0.026 (67%)             | 0.000   |
| Due to composition (%)                | 79 (61%)                | 0.000   | 0.013 (33%)             | 0.003   |
| Relative coefficient contribution (%) |                         |         |                         |         |
| Female                                | -73.5                   | 0.083   | -86.8                   | 0.000   |
| Hispanic                              | -111.4                  | 0.000   | -35.1                   | 0.006   |
| Wear time                             | 718.8                   | 0.058   | 425.7                   | 0.009   |

Notes: These four panels present results from regression decomposition analysis of four selected pairs of occupational groups. We present the relative share of the coefficient contribution of selected covariates.

Source: 2005–2006 National Health and Nutrition Examination Survey.

More importantly, our study identifies the contribution of occupational difference implicitly in tasks relative to the contribution of workers' attributes. As educational attainment is a key criterion to define occupational groups, we take a closer look into its between-occupation distribution. The occupational contribution is large when workers' average educational attainment differs between the occupations. This suggests that the physical movement requirements of occupation align with educational levels. Further, the occupational contribution is also large when workers' average educational level is similarly high. This may imply the physical movement differentiation among occupations requiring high education and technological advancement involving specialized skill trainings. Interestingly, the occupational contribution is small between two occupations when the average educational level is similarly low, conveying no physical movement differentiation among occupations with low educational requirement. Taken together of these three patterns, occupation appears to play an important role in translating education to determine PA at work.

More broadly, our findings highlight the need to intervene how occupation determines health through the occupation-PA relationship in the workplace, which is currently underdeveloped in the United States (Jochem et al., 2018; Healy & Goode, 2018). For example, the guidelines from occupational safety and health (OSH) and worksite health

promotion (WHP) have two broad goals: reduce deaths from work-related injuries and reduce work-related injuries that result in medical treatment, lost time for work, and restricted work activity (NIOSH, 2012). Apparently, risks related to occupation-based PA have not been adequately considered in the guidelines. Although lacking activity, prolonged sedentary behaviors, excessive physical movements during working hours may not induce immediate injuries, they may pose threat to workers' health in the long run, especially in terms of physical distress, musculoskeletal disorders, and later-life disability (Shockey et al., 2017; Möller et al., 2015; Missikpode et al., 2016). Therefore, OSH and WHP may consider incorporating occupation-based PA into future guidelines, which can also help mitigate the OHS disparities in quality of life across demographic and socioeconomic groups, in addition to disparities in fatal injuries (Steege et al., 2014). Specifically, distinct physical requirements defined in occupational tasks permit tailored health-promoting interventions. For example, intervention programs should pay attention to the heterogeneity among white-collar occupations, given that they are not uniformly sedentary, where workers in health and education exhibit volume of PA closer to that in service and manual occupations. Moreover, policy designers should acknowledge the nonlinear dynamics of physical behaviors: even when workers meet the volume target of PA, they may be subject to different risk factors due to the ways by which PA is accumulated at work. This requires structural approach for intervention, such as redesigning the organization of work, regulating working hours, and reducing workload to mitigate exposure to risk-related PA level and accumulation pattern, in addition to individual-level approaches on changing workers' behaviors such as exercise.

Moreover, when it comes to PA, most workplaces promote programs in the forms of physical exercise or moderate-to-vigorous activity, as a way to help workers meet the recommendations on leisure-time PA (LTPA, see Haskell et al., 2007). They also assume that workers across occupations would benefit from a 10-minute brisk walk or cycling (Centers for Disease Control and Prevention, 2012), irrespective of the physical nature of different occupations (Gudnadottir et al., 2019). Although we promote the idea of transforming work break into "booster break" (Taylor, 2005) for sedentary occupations, we call attention to the distinction between occupation-based PA and LTPA and consider their interplay. Workers fatigued from physically strenuous occupations may not necessarily benefit from high levels of LTPA, given the overloading on the cardiovascular system through prolonged intravascular turbulence and increased wall shear stress (Clays et al., 2013; Holtermann et al., 2018; Li et al., 2013). Therefore, as with our recommendations for occupation-based PA intervention, we also recommend program designers tailor the LTPA guidelines according to the level and accumulation pattern of each occupation and pay attention to the context in which PA is performed.

This study could be improved in a number of fronts when required data are available. First, diary data on detailed working hours will help analyze PA during precise work hours rather than assuming 9am-5pm for regular daytime workers. While stressing the importance of studying PA at work, equally important is to study precisely defined work intervals and work breaks. Collecting time diary data in conjunction with accelerometry data will better separate PA between work and work break. In addition, the accelerometry data provided in the 2005–2006 NHANES do not accurately measure upper body movements with stationary positions. Objectively tracking PA with both motion- and posture-sensor may further improve the measurement of occupation-based PA to inform multi-faceted ergonomic conditions of an occupation. Third, the 2005–2006 NHANES provides 22 major groups which may obscure within-occupation heterogeneity (Martin-Caughey, 2021). In addition, the sample size is not large enough to study each. More granular occupational groups with sufficiently large group sizes will enable us to depict the specific task requirements stipulated in each occupation, which will yield more powerful evidence to support the occupational determinant of PA at work, a paramount type of health

behavior.

With these caveats, our study expands the scope of occupational stratification beyond the long-standing sociological tradition focusing on income, status, and prestige in the classical occupation literature (Blau & Duncan, 1967; Warren et al., 2002). It pinpoints the contextual effect of occupation on health behavior, here PA, and in turn, health outcomes. For example, our decomposition analysis can be extended to quantify PA disparities across multiple demographic and socioeconomic groups. We found that Hispanic and black workers are concentrated in low-skilled service, manual, and health-related occupations of both high PA volume and high PA fragmentation, suggesting excessive physical movements and frequent sedentary breaks. These objective PA measures may help investigate the role of occupational segregation in driving the documented racial/ethnic disparities in physical performance, functional limitations, and disability (Pebley et al., 2021; Haas et al., 2012; Melvin et al., 2014). Continuous effort must be made to provide systematic evidence of the pathway from occupation to PA to health outcomes.

## 6. Conclusion

The present study provides evidence for the occupational determinant of PA in the workplace by exploiting the availability of accelerometer data and work schedule in a nationally representative survey. Our work makes a theoretical contribution to the physical nature of occupational context and a measurement contribution to PA-related research. It is our hope that these contributions will boost future research related to occupation, PA, and health outcomes, especially in the era of big data where objective data are increasingly available on occupation-based health behaviors and health outcomes of American workforce.

## Funding disclosure

This research was supported by Hopkins Population Center and its infrastructure grant (P2CHD042854) from the National Institute of Child Health and Human Development (NICHD), United States.

## Ethnical approval

All individual level data used in the research article is secondary data and publicly available, which is collected by CDC National Center for Health Statistics.

## Authorship contribution statement

**Xiao Yu:** Conceptualization, Methodology, Formal analysis and investigation, Data interpretation, Visualization, Writing - original draft preparation, Writing - review & editing.

**Lingxin Hao:** Conceptualization, Methodology, Data interpretation, Writing - original draft preparation, Writing - review & editing, Supervision, Funding acquisition.

**Ciprian Crainiceanu:** Conceptualization, Data interpretation, Critical feedback, Supervision.

**Andrew Leroux:** Conceptualization, Methodology, Software, Data interpretation, Critical feedback, Writing - review & editing.

## Declaration of competing interest

The authors declare no competing interests.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ssmph.2021.100989>.

## References

- Abdel Hadi, S., Mojzisch, A., Parker, S. L., & Häusser, J. A. (2021). Experimental evidence for the effects of job demands and job control on physical activity after work. *Journal of Experimental Psychology: Applied*, 27(1), 125–141. <https://doi.org/10.1037/xap0000333>
- Anisworth, B. E., Richardson, M. T., Jacobs, D. R., Leon, A. S., & Sternfeld, B. (1999). Accuracy of recall of occupational physical activity by questionnaire. *Journal of Clinical Epidemiology*, 52(3), 219–227. [https://doi.org/10.1016/S0895-4356\(98\)00158-9](https://doi.org/10.1016/S0895-4356(98)00158-9)
- Beenackers, M. A., Kamphuis, C. B. M., Giskes, K., Brug, J., Kunst, A. E., Burdorf, A., & van Lenthe, F. J. (2012). Socioeconomic inequalities in occupational, leisure-time, and transport related physical activity among European adults: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, 9, 116. <https://doi.org/10.1186/1479-5868-9-116>
- Blau, F. D., Brummund, P., & Liu, A. Y. H. (2013). Trends in occupational segregation by gender 1970-2009: Adjusting for the impact of changes in the occupational coding system. *Demography*, 50(2), 471–492. <https://doi.org/10.1007/s13524-012-0151-7>
- Blau, P. M., & Duncan, O. D. (1967). *The American occupational structure*. New York: John Wiley & Sons.
- Blinder, A. S. (1973). Wage discrimination: Reduced form and structural estimates. *Journal of Human Resources*, 8, 436–455. <https://doi.org/10.2307/144855>
- Brownson, R. C., Boehmer, T. K., & Luke, D. A. (2005). Declining rates of physical activity in the United States: What are the contributors? *Annual Review of Public Health*, 26, 421–443. <https://doi.org/10.1146/annurev.publhealth.26.021304.144437>
- Burgard, S. A., & Lin, K. Y. (2013). Bad jobs, bad health? How work and working conditions contribute to health disparities. *American Behavioral Scientist*, 57(8), 1105–1127. <https://doi.org/10.1177/0002764213487347>
- Centers for Disease Control and Prevention. (2012). *Steps to wellness: A guide to implementing the 2008 physical activity guidelines for Americans in the workplace*. Atlanta: U.S. Department of Health and Human Services. [https://www.cdc.gov/physicalactivity/worksites-pa/pdf/steps2wellness\\_broch14\\_508\\_tag508\\_tag508.pdf](https://www.cdc.gov/physicalactivity/worksites-pa/pdf/steps2wellness_broch14_508_tag508_tag508.pdf)
- Clays, E., De Bacquer, F., Janssens, H., De Clercq, B., Casini, A., Braeckman, L., Kittel, F., De Backer, G., & Holtermann, A. (2013). The association between leisure time physical activity and coronary heart disease among men with different physical work demands: A prospective cohort study. *European Journal of Epidemiology*, 28, 241–247. <https://doi.org/10.1007/s10654-013-9764-4>
- Dempsey, P., Larsen, R. N., Sethi, P., Sacre, J. W., Straznicki, N. E., Cohen, N. D., Cerin, E., Lambert, G. W., Owen, N., Kingwell, B. A., & Dunstan, D. W. (2016). Benefits for type 2 diabetes of interrupting prolonged sitting with brief bouts of light walking or simple resistance activities. *Diabetes Care*, 39, 964–972. <https://doi.org/10.2337/dc15-2336>
- Deyaert, J., Harms, T., Weenas, D., Gershuny, J., & Glorieux, I. (2017). Attaching metabolic expenditures to standard occupational classification systems: Perspectives from time-use research. *BMC Public Health*, 17, 620. <https://doi.org/10.1186/s12889-017-4546-7>
- Diaz, K., Howard, V. J., Hutto, B., Colabianchi, N., Vena, J. E., Safford, M. M., Blair, S. N., & Hooker, S. P. (2017). Patterns of sedentary behavior and mortality in U.S. Middle-aged and older adults. *Annals of Internal Medicine*, 167, 465–475. <https://doi.org/10.7326/M17-0212>
- Di, J., Leroux, A., Urbanek, J., Varadhan, R., Spira, A. P., Schrack, J., & Zipunnikov, V. (2019). *Patterns of sedentary and active time accumulation are associated with mortality in US adults: The NHANES study*. bioRxiv. <https://doi.org/10.1101/182337>
- Gerstel, N., & Clawson, D. (2018). Control over time: Employers, workers, and families shaping work schedules. *Annual Review of Sociology*, 44, 77–97. <https://doi.org/10.1146/annurev-soc-073117-041400>
- Green, F. (2012). Employee involvement, technology and evolution in job skills: A task-based analysis. *Industrial and Labor Relations Review*, 65(1), 36–67. <https://doi.org/10.1177/2F001979391206500103>
- Gryzywacz, J. G., Segel-Karpas, D., & Lachman, M. E. (2016). Workplace exposures and cognitive function during adulthood: Evidence from national survey of midlife development and the O\*NET. *Journal of Occupational and Environmental Medicine*, 58(6), 535–541. <https://doi.org/10.1097/JOM.0000000000000727>
- Gudnadottir, U., Cadmus-Bertram, L., Spicer, A., Gorzelitz, J., & Malecki, K. (2019). The relationship between occupational physical activity and self-reported vs. Measured total physical activity. *Preventive Medicine Reports*, 15, 100908. <https://doi.org/10.1016/j.pmedr.2019.100908>
- Haas, S., Krueger, P. M., & Rohlfsen, L. (2012). Race/ethnic and nativity disparities in later life physical performance: The role of health and socioeconomic status over the life course. *Journal of Gerontology, Series B*, 67(2), 238–248. <https://doi.org/10.1093/geronb/gbr155>
- Hadgraft, N. T., Dunstan, D. W., & Owen, N. (2018). *Models for understanding sedentary behavior in sedentary behavior epidemiology*. Springer Series on Epidemiology and Public Health.
- Hallman, D. M., Jørgensen, M. B., & Holtermann, A. (2017). On the health paradox of occupational and leisure-time physical activity using objective measurements: Effects on autonomic imbalance. *PLoS One*, 12(5), Article e0177042. <https://doi.org/10.1371/journal.pone.0177042>
- Haskell, W. L., Lee, I. M., Pate, R. R., Powell, K. E., Blair, S. N., Franklin, B. A., Macera, C. A., Heath, G. W., Thompson, P. D., & Bauman, A. (2007). Physical activity and public health: Updated recommendation for adults from the American college of sports medicine and the American heart association. *Circulation*, 116(9), 1081–1093. <https://doi.org/10.1249/mss.0b013e3180616b27>

- Healy, G. N., & Goode, A. D. (2018). *Workplace programs aimed at limiting occupational sitting in sedentary behavior epidemiology*. Springer Series on Epidemiology and Public Health.
- Holtermann, A., Krause, N., van der Beek, A. J., & Straker, L. (2018). The physical activity paradox: Six reasons why occupational physical activity (OPA) does not confer the cardiovascular health benefits that leisure time physical activity does. *British Journal of Sports Medicine*, 52, 149–150. <https://doi.org/10.1136/bjsports-2017-097965>
- Jochem, C., Schmid, D., & Leitzmann, M. F. (2018). *Introduction to sedentary behavior epidemiology in sedentary behavior epidemiology*. Springer Series on Epidemiology and Public Health.
- Kim, J., Tanabe, K., Yokoyama, N., Zempo, H., & Kuno, S. (2013). Objectively measured light-intensity lifestyle activity and sedentary time are independently associated with metabolic syndrome: A cross-sectional study of Japanese adults. *International Journal of Behavioral Nutrition and Physical Activity*, 10(1), 30. <https://doi.org/10.1186/1479-5868-10-30>
- Kirk, M. A., & Rhodes, R. (2011). Occupation correlates of adults' participation in leisure-time physical activity: A systematic review. *American Journal of Preventive Medicine*, 40(4), 476–485. <https://doi.org/10.1016/j.amepre.2010.12.015>
- Krause, N., Brand, R. J., Arah, O. A., & Kauhanen, J. (2015). Occupational physical activity and 20-year incidence of acute myocardial infarction: Results from the kuopio ischemic heart Disease risk factor study. *Scandinavian Journal of Work, Environment & Health*, 41(2), 124–139. <https://doi.org/10.5271/sjweh.3476>
- Leitzmann, M. F., Jochem, C., & Schmid, D. (2018). *Sedentary behavior epidemiology*. Springer Series on Epidemiology and Public Health.
- Leroux, A., Di, J., Smirnova, E., McGuffey, E., Cao, Q., Bayatmokhtari, E., Tabacu, L., Zipunnikov, V., Urbanek, J. K., & Crainiceanu, C. (2019). Organizing and analyzing the activity data in NHANES. *Statistics in Biosciences*, 11(2), 262–287. <https://doi.org/10.1007/s12561-018-09229-9>
- Leroux, A., Xu, S., Kundu, P., Muschelli, J., Smirnova, E., Chatterjee, N., & Crainiceanu, C. (2021). *Journals of Gerontology - Series A Biological Sciences and Medical Sciences*, 76(8), 1486–1494. <https://doi.org/10.1093/geron/glaa250>
- Li, J., Loebroks, A., & Angerer, P. (2013). Physical activity and risk of cardiovascular Disease: What does the new epidemiological evidence show? *Current Opinion in Cardiology*, 28(5), 575–583. <https://doi.org/10.1097/HCO.0b013e328364289c>
- Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of Disease. *Journal of Health and Social Behavior*, 80–94. <https://doi.org/10.2307/2626958>
- Lohne-Seiler, H., Hansen, B. H., Kollé, E., & Andersen, S. A. (2014). Accelerometer-derived physical activity and self-reported health in a population of older adults (65–85 years): A cross-sectional study. *BMC Public Health*, 14, 284. <https://doi.org/10.1186/1471-2458-14-284>
- Maes, I., Ketels, M., Van Dyck, D., & Clays, E. (2020). The occupational sitting and physical activity questionnaire (ospaq): A validation study with accelerometer-assessed measures. *BMC Public Health*, 20, 1072. <https://doi.org/10.1186/s12889-020-09180-9>
- Mailey, E. L., Rosenkranz, S. K., Casey, K., & Swank, A. (2016). Comparing the effects of two different break strategies on occupational sedentary behavior in a real world setting: A randomized trial. *Preventive Medicine Reports*, 4, 423–428. <https://doi.org/10.1016/j.pmedr.2016.08.010>
- Martin-Caughey, A. (2021). What's in an occupation? Investigating within-occupation variation and gender segregation using job titles and task descriptions. *American Sociological Review*, 86(5), 960–999. <https://doi.org/10.1177/00031224211042053>
- Martinez, W. (2019). How science and technology developments impact employment and education. *Proceedings of the National Academy of Sciences*, 115(50), 12624–12629. <https://doi.org/10.1073/pnas.1803216115>
- Melvin, J., Hummer, R. A., Elo, I. T., & Mehta, N. (2014). Age patterns of racial/ethnic/nativity differences in disability and physical functioning in the United States. *Demographic Research*, 31(17), 497–510. <https://doi.org/10.4054/DemRes.2014.31.17>
- Mirowsky, J., & Ross, C. E. (2015). Education, health, and the default American lifestyle. *Journal of Health and Social Behavior*, 56(3), 297–306. <https://doi.org/10.1177/0022146515594814>
- Missikpode, C., Michael, Y. L., & Wallace, R. B. (2016). Midlife occupational physical activity and risk of disability later in life: National health and aging trends study. *Journal of the American Geriatrics Society*, 64(5), 1120–1127. <https://doi.org/10.1111/jgs.14083>
- Møller, A., Reventlow, S., Hansen, Å. M., Andersen, L., Siersma, V., Lund, R., Avlund, K., Andersen, J. H., & Mortensen, O. S. (2015). Does physical exposure throughout working life influence chair-rise performance in midlife? A retrospective cohort study of associations between work and physical function in Denmark. *BMJ Open*, 5, Article e009873. <https://doi.org/10.1136/bmjopen-2015-009873>
- Mutz, M., Abdel Hadi, S., & Häusser, J. A. (2020). Work and sport: Relationships between specific job stressors and sports participation. *Ergonomics*, 63(9), 1077–1087. <https://doi.org/10.1080/00140139.2020.1772381>
- NIOSH. (2012). *Research compendium: The NIOSH total worker Health™ program: Seminal research papers 2012*. Washington, DC: U.S. Department of Health and Human Services, Public Health Service, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health, DHHS (NIOSH) Publication. No. 2012-146, 2012 May:1-214 <https://www.cdc.gov/niosh/docs/2012-146/pdfs/2012-146.pdf?cid=10.26616/NIOSH/PUB2012146>
- Oaxaca, R. L. (1973). Male-female wage differentials in urban labor markets. *International Economic Review*, 14, 693–709. <https://doi.org/10.2307/2525981>
- Pebley, A. R., Goldman, N., Andrasfay, T., & Pratt, B. (2021). Trajectories of physical functioning among older adults in the US by race, ethnicity, and nativity: Examining the role of working conditions. *PLoS One*, 16(3), Article e0247804. <https://doi.org/10.1371/journal.pone.0247804>
- Phelan, J. C., Link, B. G., & Tehranifar, P. (2010). Social conditions as fundamental causes of health inequalities: Theory, evidence, and policy implications. *Journal of Health and Social Behavior*, 51(1 suppl), S28–S40. <https://doi.org/10.1177/0022146510383498>
- Pulakka, A., Stenholm, S., Bosma, H., Schaper, N. C., Savelberg, H. H. C. M., Stehouwer, C. D. A., van der Kallen, C. J. H., Dagnelie, P. C., Sep, S. J. S., & Koster, A. (2018). Association between employment status and objectively measured physical activity and sedentary behavior – the maastricht study. *Journal of Occupational and Environmental Medicine*, 60(4), 309–315. <https://doi.org/10.1097/JOM.000000000000125>
- Quinn, T. D., Gabriel, K. P., Siddique, J., Aaby, D., Whitaker, K. M., Lane-Cordova, A., Sidney, S., Stemfield, B., & Gibbs, B. B. (2020). Sedentary time and physical activity across occupational classifications. *American Journal of Health Promotion*, 34(3), 247–256. <https://doi.org/10.1177/0890117119885518>
- Reider, L., Bai, J., Scharfstein, D. O., & Zipunnikov, V. (2020). Methods for step count data: Determining “valid” days and quantifying fragmentation of walking bouts. *Gait & Posture*, 81, 205–212. <https://doi.org/10.1016/j.gaitpost.2020.07.149>
- del Río, del C., & Alonso-Villar, O. (2015). The evolution of occupational segregation in the United States, 1940–2010: Gains and losses of gender-race/ethnicity groups. *Demography*, 52(3), 967–988. <https://doi.org/10.1007/s13524-015-0390-5>
- Ruggles, S. (2015). Patriarchy, power, and pay: The transformation of American families, 1800–2015. *Demography*, 52, 1797–1823. <https://www.jstor.org/stable/43699138>
- Schneider, D., & Harknett, K. (2019). Consequences of routine work-schedule instability for worker health and well-being. *American Sociological Review*, 84(1), 82–114. <https://doi.org/10.1177/0003122418823184>
- Shockey, T. M., Zack, M., & Sussell, A. (2017). Health-related quality of life among US workers: Variability across occupation groups. *American Journal of Public Health*, 107(8), 1316–1323. <https://doi.org/10.2105/AJPH.2017.303840>
- Smimova, E., Leroux, A., Cao, Q., Tabacu, L., Zipunnikov, V., Crainiceanu, C., & Urbanek, J. K. (2020). The predictive performance of objective measures of physical activity derived from accelerometry data for 5-year all-cause mortality in older adults: National health and nutritional examination survey 2003–2006. *Journal of Gerontology: Medical Science*, 75(9), 1779–1785. <https://doi.org/10.1093/geron/glz193>
- Steege, A. L., Baron, S. L., Marsh, S. M., Menéndez, C. C., & Myers, J. R. (2014). Examining occupational health and safety disparities using national data: A cause for continuing concern. *American Journal of Industrial Medicine*, 57, 527–538. <https://doi.org/10.1002/ajim.22297>
- Steeves, A. J., Tudor-Locke, C., Murphy, R. A., King, G. A., Fitzhugh, E. C., & Harris, T. B. (2015). Classification of occupational activity categories using accelerometry: Nhanes 2003–2004. *International Journal of Behavioral Nutrition and Physical Activity*, 12, 89. <https://doi.org/10.1186/s12966-015-0235-z>
- Steeves, A. J., Tudor-Locke, C., Murphy, R. A., King, G. A., Fitzhugh, E. C., Bassett, D. R., Domelen, D. V., Schuna, J. M., Jr., & Harris, T. B. (2018). Daily physical activity by occupational classifications in US adults: Nhanes 2005–2006. *Journal of Physical Activity and Health*, 15, 900–911. <https://doi.org/10.1123/jpah.2017-0465>
- Taylor, W. C. (2005). Transforming work breaks to promote health. *American Journal of Preventive Medicine*, 29(5), 461–465. <https://doi.org/10.1016/j.amepre.2005.08.040>
- Toch, M., Bamba, C., Lunau, T., van Der Wel, K. A., Witvliet, M. I., Dragano, N., & Eikemo, T. A. (2014). All part of the job? The contribution of the psychosocial and physical work environment to health inequalities in Europe and the European health divide. *International Journal of Health Services*, 44(2), 285–305. <https://doi.org/10.2190/H5.44.2.g>
- Tudor-Locke, C., Washington, T. L., Ainsworth, B. E., & Troiano, R. P. (2011). Assigning metabolic equivalent values to the 2002 census occupational classification system. *Journal of Physical Activity and Health*, 8, 581–586. <https://doi.org/10.1123/jpah.8.4.581>
- Varma, V. R., Dey, D., Leroux, A., Di, J., Urbanek, J., Xiao, L., & Zipunnikov, V. (2018). Total volume of physical activity: TAC, TLAC or TAC(Δ). *Preventive Medicine*, 106, 233–235. <https://doi.org/10.1016/j.ypmed.2017.10.028>
- Wanigatunga, A. A., Di, J., Zipunnikov, V., Urbanek, J., Kuo, P. L., Simonsick, E. M., Ferrucci, L., & Schrack, J. A. (2019). Association of total daily physical activity and fragmented physical activity with mortality in older adults. *JAMA Network Open*, 2(10), Article e1912352. <https://doi.org/10.1001/jamanetworkopen.2019.12352>
- Warren, J. R., Sheridan, J. T., & Hauser, R. M. (2002). Occupational stratification across the life course: Evidence from the Wisconsin longitudinal study. *American Sociological Review*, 67(3), 432–455. <https://doi.org/10.2307/3088965>
- Weeden, K. A., & Grusky, D. B. (2012). The three worlds of inequality. *American Journal of Sociology*, 117(6), 1723–1785. <https://doi.org/10.1086/665035>
- Wolff-Hughes, D. L., Fitzhugh, E. C., Bassett, D. R., & Churilla, J. R. (2015). Total activity counts and bouted minutes of moderate-to-vigorous physical activity: Relationships with cardiometabolic biomarkers using 2003–2006 NHANES. *Journal of Physical Activity and Health*, 12, 694–700. <https://doi.org/10.1123/jpah.2013-0463>
- Yun, M. S. (2005a). Hypothesis tests when decomposing differences in the first moment. *Journal of Economic and Social Measurement*, 30, 295–304. <https://doi.org/10.3233/JEM-2005-0257>
- Yun, M. S. (2005b). A simple solution to the identification problem in detailed wage decompositions. *Economic Inquiry*, 43, 766–772. <https://doi.org/10.1093/ei/cbi053>