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Racial, Ethnic, and Gender Differences in Physical Activity

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Abstract

This study examines racial, ethnic and gender (REG) differentials in physical activity (PA), a significant input into health production and human capital investments. Prior studies have relied on leisure-time activity, which comprises less than 10% of non-work PA and does not capture specific information on intensity or duration, thus presenting an incomplete and potentially-biased picture of how various modes of PA differ across REG groups. This study addresses these limitations by constructing detailed and all-inclusive PA measures from the American Time Use Surveys, which capture the duration of each activity combined with its intensity based on the Metabolic Equivalent of Task. Estimates suggest significant REG differentials in work-related and various modes of non-work PA, with 30–65% of these differentials attributed to differences in education, socioeconomic status, time constraints, and locational attributes. These conditional PA differentials are consistent with and may play a role in observed REG disparities in health outcomes.

Keywords

physical activity; race; gender; ethnicity; disparities; health; exercise

1. Introduction

Health capital and knowledge-based human capital are intrinsically linked in both directions, within families and individuals, and across generations. Since education augments the production of health capital (Grossman, 1972), lower human capital accumulation can result in poorer health as adults. Several studies have pointed to the role of maternal health behaviors and circumstances during early childhood in leading to health disparities among

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children. Not only are poor children more likely to have chronic conditions, they are also more likely to be hospitalized and recover more slowly than richer children (Currie and Stabile, 2003). Such disparities in health may further contribute to differences in the accumulation of human capital. In addition, poor health in childhood can have lasting effects on educational attainment and human capital accumulation, and play a role in the inter-generational transfer of economic status and well-being (Ehrlich and Lui, 1991; Case et al., 2005; Currie, 2009; Jackson, 2009).

This study examines racial, ethnic and gender (REG) differentials in physical activity (PA), a significant input into health production, and assesses the effects of various socioeconomic factors on these differentials. Understanding differentials in PA is important since there is an extensive literature which finds that PA has significant direct and indirect effects on health, an essential component of human capital. Evidence from epidemiologic studies, cohort-based studies, cross-sectional analyses and randomized trials suggests that a physically-active lifestyle can reduce mortality and morbidity. For instance, physical activity, and specifically consistent physical activity, appears to directly protect against depression, hypertension, diabetes, and heart disease, even after controlling for body mass index, as well as indirectly promote heart health by protecting against obesity (Lawlor and Hopker, 2001; Colman and Dave, 2012). There also appears to be a dose-response relation with generally higher levels of PA and cardio-respiratory fitness leading to larger decreases in morbidity and mortality rates (Colman and Dave, 2012).

REG differentials in PA may also contribute to the persistent REG differentials in health. According to the National Center for Health Statistics (2007), mortality from heart disease is over 30% higher among Blacks relative to Whites, and is more than double for diabetes. Among American Indians/Alaskan Natives and Hispanics, diabetes-related mortality is significantly higher relative to Whites. Furthermore, racial gaps in cancer-related, heart disease-related and diabetes-related mortality have generally failed to narrow over the past four decades.[1] A number of studies have investigated the underlying causes of this race/ethnic and socioeconomic status-related health gradient (Farmer and Ferraro, 2005; Cutler, Lleras-Muney, and Vogl, 2011), examining, for instance, racial and ethnic differences in income and education, smoking and drinking prevalence, participation in other risky activities, and access to less or lower-quality medical care. However, the association between race/ethnicity and health persists even within similar income categories and among insured individuals. Thus, accounting for these observed differences across race and ethnic groups does not fully explain the gap.

One understudied factor that contributes to health capital production, and which may partly explain the persistent REG differentials in health, is engagement in PA and various types of PA. An extensive literature suggests that non-work modes of PA in particular have significant direct and indirect effects on physical and mental health. According to USDHHS (2002) the number of Americans with chronic illnesses that may be averted or improved through regular PA include: 12.6 million individuals with coronary heart disease; 1.1 million

[1]Woolf et al. (2004) estimate that, between 1991 and 2000, if the mortality rates of African-Americans were the same as Whites, there would have been 886,902 fewer deaths. This is five times the number of deaths averted through medical advances.

individuals who experience a heart attack in a given year; 15 million individuals who have type 2 diabetes plus 16 million more individuals who are ‘pre-diabetic’; 107,000 individuals who are newly diagnosed with colon cancer each year; 300,000 individuals who incur hip fractures each year; 50 million individuals afflicted with hypertension; and 61% of the adult population who are either obese or overweight. The USDHHS (2002) also notes that regular PA can reduce morbidity and mortality from mental health disorders.

Some studies (Mummery et al. 2005; King et al. 2001; Futon-Kehoe et al. 2001) find that all forms of non-work PA reduce mortality and various forms of morbidity. PA also occurs through market work although this type of PA may be less beneficial or even have adverse effects on health. Studies by Kukkonen-Harjula (2007) and Virkkunen et al. (2005), for instance, conclude that work-related PA can have detrimental effects on cardiovascular health possibly due to the high and sustained energetic demands of some types of work (for instance, in construction and mining industries, and agriculture). This strong association between PA and mental and physical health outcomes suggests that REG differentials in PA may underlie REG differentials in health.

Estimates from the 2007 National Health Interview Survey (NHIS) indicate significant differences in PA across racial groups. For instance, 33.8% of Whites, 23.8% of Hispanics and 23.2% of Blacks engage in regular leisure PA. However, the NHIS and other previously used national surveys (such as the Behavioral Risk Factor Surveillance System-BRFSS; National Health and Nutrition Examination Surveys-NHANES) are limited in their measures of PA. Most prior studies, based on these surveys, have measured only leisure PA, and generally overlooked other forms of PA including active forms of commuting to work, PA in home maintenance, shopping, child care and many other daily activities. An exclusive focus on leisure PA may lead to biased conclusions. Many of the national datasets employed in the prior work include only subjective and retrospective measures of participation in leisure PA, which may be prone to recall bias and reference bias (for instance, cross-person differences in what constitutes “moderate” or “vigorous” activity, which is what is typically probed in these surveys). These measures also generally do not capture specific information on the duration or intensity of the engaged activities. Data from the American Time Use Surveys (ATUS) indicate that leisure PA comprises only about 10% of total non-work PA. Furthermore, due to substitution between various forms of PA, individuals who have lower leisure PA may not necessarily have lower total non-work PA or total PA.

This study addresses these issues by utilizing the American Time Use Surveys (ATUS) to more accurately measure all forms of PA undertaken by the individual, measures which capture both the duration and intensity of the PA, bypass reference bias, maximize recall, and minimize measurement error. This study is the first to provide estimates of REG differentials across these various types of PA, based on detailed measures constructed from the ATUS. Models further assess whether, and the extent to which, REG differentials in PA can be accounted for by observed individual differences in human capital, work status, other person-specific socioeconomic factors, and differences in location and environmental attributes. These specifications also investigate the degree to which work-related PA, which significantly differs across race, ethnicity, and gender, substitutes for or complements other types of PA.

While this study presents the first estimates of REG differentials across these various types of PA, and documents the extent to which these differentials can be explained by observable human capital, socioeconomic and environmental characteristics, a full structural model which endogenizes all of these factors is beyond the scope of this study. The purpose of the estimates is to provide a detailed study of how various modes of PA vary across race, ethnicity, and gender, and assess the factors that may potentially drive these differences. Though we do not claim a complete causal framework, we highlight some plausible causal connections that may underlie the associations as warranted.

Based on superior and all-inclusive measures of PA, the results from this study indicate that work-based physical activity is significantly lower among Asians, on the order of about 10% relative to the sample mean, and higher among all other racial/ethnic groups, on the order of 9–15%, relative to non-Hispanic Whites. Work physical activity is also significantly higher among males. Non-work physical activity tends to be significantly lower by about 26% for Blacks, by about 10% among Hispanics, and by about 6% among other racial groups, in comparison to non-Hispanic Whites, and is about 12% lower for males than for females. Disaggregated measures of non-work PA, relating to leisure and recreation, household activities, active travel, and other activities, also show significant REG differences. Approximately 30–60% of the differentials in non-work physical activity across racial/ethnic groups and 37% of the gender differential can be attributed to differences in education, socioeconomic status, proxies for time constraints, and locational attributes, though persistent differences remain even after controlling for these factors. With respect to work PA among employed individuals, these factors account for about 50–65% of the race/ethnic differentials and 23% of the gender differential. Prior studies have shown that non-work physical activity has a positive impact on health while work physical activity may have muted or even adverse effects for some individuals. We find similar associations between self-assessed health and our comprehensive measures of work and non-work PA. The adjusted differentials in physical activity from this study are consistent with observed racial, ethnic and gender disparities in health outcomes.

2. Literature

A number of prior studies have documented REG differentials in PA. Using data from the 1987 National Medical Expenditure Survey (NMES), Hersch (1996) finds that Black females are least likely to participate in moderate to strenuous exercise, followed by White females and Black males. The highest prevalence is among White males. Jones et al. (1998) utilize the 1990 NHIS to examine the prevalence of adults who meet recommended guidelines for moderate PA. They find that only about one-third of the U.S. population meets these recommendations, with women, ethnic minorities, low-educated adults, and older adults being the least active. Brownson et al. (2000) conduct telephone surveys among 2,912 U.S. women 40 years of age and older, based on a sampling plan similar to the BRFSS. They note that leisure PA was lowest among Blacks and American Indians/Alaskan Natives. He and Baker (2005) examine differences in leisure and work PA among older adults from the 1992 Health and Retirement Study, across racial and ethnic minority groups. Leisure PA was lower among Blacks and Hispanics compared to Whites and steadily declined with lower levels of education. However, work PA showed the reverse pattern, being lowest among Whites and persons with greater education.

Some studies have examined corollary REG differences in inactivity. Crespo et al. (2000), for instance, estimate race/ethnic-specific prevalence of leisure physical inactivity based on the 3rd NHANES 1988–1994. They find the highest rate of leisure inactivity among Mexican-Americans, followed by Blacks and then Whites. Marshall et al. (2007) study the prevalence of leisure physical inactivity as well as the relationship between leisure inactivity and occupational PA across racial/ethnic groups and across social class indicators, based on the 2002 National Physical Activity and Weight Loss Survey (which uses self-reported PA questions from the BRFSS). Estimates indicate that leisure inactivity is lower among White men and women relative to non-Hispanic Black men and women. Highest rates of inactivity were found among Hispanic men and women. Leisure PA had no relationship to occupational PA except for the most strenuous occupational work for Hispanics. Education is found to be an important mediator in the link between race/ethnicity and leisure physical inactivity.

Hawkins et al. (2009) study 2,688 individuals, selected from the 10,122 individuals in the 2003–2004 NHANES, who carried accelerometers.[2] They find that PA decreases with age for both men and women across all racial/ethnic groups. Men are more active than women, with the exception of Hispanic women. Hispanic women are more active at ages 40–59 compared to younger or older ages. Hispanic men engage in more total PA and light-intensity PA relative to their White and Black counterparts for all age groups. These estimates may not be generalizable due to the selected sample. These results also contrast with those from other studies that relied on self-reported leisure PA, and underscore the importance of using superior measures of unstructured PA that cannot be assumed to be homogenous across population subgroups.

A second strand of literature has investigated the determinants of PA, including environmental characteristics, income and education. Gordon-Larsen et al. (2006) study the relationship between the availability of recreational facilities and PA among adolescents. They find that lower-SES and high-minority areas had reduced access to facilities, which in turn was associated with decreased PA. Humpel, Owen and Leslie (2002) review 19 quantitative studies on the relationship between PA and environmental attributes. They conclude that access and aesthetic attributes are significantly associated with PA, while weather and safety-related attributes show a weaker relationship. Reviews of approximately 300 studies on the correlates of adult PA were performed by Bauman et al. (2002) and Sherwood and Jeffery (2000). These reviews conclude that males and Whites tend to be more physically active, and that income, education, and socioeconomic status are generally positively associated with PA. They also indicate that access to PA-supportive facilities tend to increase participation whereas adverse seasons and climate negatively impact PA. The general consensus from this literature is that environmental characteristics and measures of income and education are important correlates of all types of PA. However, causality is not

[2]The accelerometer used in NHANES is a small electrical device carried by the subject, which detects and stores the intensity of all movements and activity per one minute time intervals.

well-established due to sample selection issues, unobserved heterogeneity, and simultaneity bias.

A major limitation in both strands of literature concerns the measurement of PA. Most of the studies have relied on surveys such as the BRFSS, NHIS, NMES or the NHANES wherein measures of PA are limited to self-reported participation in “moderate” or “vigorous” leisure PA in the past week or past month. In addition to potential recall bias due to the retrospective nature of the questions, these measures also do not specifically reflect the duration and intensity of the activity. Such measures are further plagued by potential reference bias since what one respondent interprets as “moderate” or “vigorous” activity may differ from other respondents. Furthermore, most of the studies have utilized measures of leisure PA, which constitutes only about 5% of total PA and 10% of total non-work PA. Due to potential substitutions between leisure and other PA, lower levels of leisure PA may not necessarily translate into lower total PA. Thus, currently available REG differentials based on these limited constructs of PA may be biased and yield an incomplete picture of differences in total PA and other modes of PA. Many of the prior studies have also used relatively small and/or selected samples, which further limit their precision and external validity.

Furthermore, research on the determinants of PA, differentially by REG groups, is limited. While studies have shown differences in PA across racial groups (albeit based on subpar measures of PA) and other studies have shown income, education and environmental factors to be important correlates of PA, these two strands have generally remained separate. The literature is limited in its investigation of whether, and to what extent, REG differences in PA are related to differences in education, income, and environmental exposure.

This study addresses these limitations and utilizes a nationally-representative sample derived from the 2003–2009 American Time Use Surveys (ATUS). The ATUS yields a sufficiently large nationally-representative sample (approx. 98,000 observations) to reliably estimate differentials across REG subgroups. Importantly, all physical activities and their duration are carefully recorded for a specific diary day. Since specific PAs are identified in the ATUS, measures (described in the next section) are constructed to capture all types of PA including leisure PA, active travel PA, home PA, work-related PA and other PA, and which reflect both the duration and intensity of these activities. Unlike other national surveys, the ATUS is not limited to telephone-based households. Approximately five percent of the ATUS consists of respondents that did not provide a telephone number which enhances the representativeness of the data. The ATUS also includes extensive information on individual demographics and socioeconomic characteristics. To the best of our knowledge, this study provides the first estimates of REG differentials across all types of PA, using data from the ATUS and investigates the extent to which these differentials are driven by individual human capital and environmental factors.

A further advantage of the ATUS is that the intensity for each type of activity can be assigned. The intensity of each PA is an important input with respect to effects on health. There is evidence that vigorous activities, but not light activities, are associated with longevity and that the gains in life expectancy are twice as large for vigorous relative to moderate-intensity activities (Lee, 1995; Franc, 2005). Recent studies by Meltzer and Jena (2010), based on the NHANES, and by Maruyama and Yin (2012), based on the Australian National Health Survey, utilized information on the intensity of leisure PA to explore the relationship between the opportunity cost of time and intensity of exercise. Meltzer and Jena (2010) developed a model in which individuals with higher wage rates have an incentive to exercise more intensively but for shorter periods of time. They and Maruyama and Yin (2012) explored this prediction by using family income, personal income, or education as a proxy for the wage rate. These measures were found to have positive effects on the intensity of leisure PA, as predicted, but also on duration, which is counter to higher opportunity costs. These two studies differ from ours because they do not consider non-leisure PA, which comprises about 95% of total PA, and are based on past-month (Meltzer and Jena) or past-two weeks (Maruyama and Yin) recalled measures of leisure PA. While the focus of our study is on comprehensive and all-inclusive measures of all types of physical activities, that combine both the duration and intensity of each activity, we also present supplementary models that explore effects separately for duration and intensity and some of the trade-off between the two. Furthermore, since wage and non-wage income will have different effects on time allocation, particularly time spent working, the specifications separate out the effects of these two sources of income.

3. Framework

The objective of this study is to assess REG differentials in PA, and the extent to which various individual and external factors impact PA and contribute to these differentials. This question can be framed within the human capital model for the demand for health (Grossman, 1972). Grossman combines the household production model of consumer behavior with the theory of human capital investment to analyze an individual's demand for health capital. In this paradigm, individuals demand health for its consumptive and investment aspects. That is, health capital directly increases utility and also reduces work loss due to illness, consequently increasing healthy time and raising earnings.[3] The individual maximizes an intertemporal utility function that contains health and other household goods as arguments.

Health is produced with market goods (x) and the individual's time (t). One way in which time can be used to produce health is through PA.[4] PA is defined as the product of energy expenditure, per unit of time, and the amount of time engaged in the activity (t_{pa}). The energy expenditure of an activity is known as the metabolic equivalent of task (MET), which measures the energy expenditure of a given activity relative to the energy expenditure at rest. Equation (1) thus denotes the health production function with PA as an input, defined as t_{pa}*MET, and with time spent in other health-related activities (t_{other}) and market goods (x; for instance, medical care, gym membership, etc.) as other inputs. The efficiency parameter is denoted by E, which plays a similar role to technology in the firm's production process.

[3]Investment in health capital may also raise earnings by raising the marginal product of labor and consequently the wage rate.

[4]PA can also directly enter the utility function. We abstract from this possibility for convenience, and our general conclusions are not materially affected if certain forms of activities are utility-enhancing.

$$H=H(t_{pa}{}^{*}MET, t_{other}, x;E) \quad (1)$$

The individual's cost constraint is represented by equation (2):

$$F=px+wt_h \quad (2)$$

Total production costs (F) equal the costs of market inputs, valued at market price *p*, and the cost of time inputs, with t_h representing total time devoted to health production (t_{pa} + t_{other}) valued at the wage rate *w*.[5]

Maximization of a utility function that contains health and other arguments, subject to production and resource constraints, yields reduced-form demand functions for health and various types of non-work PA. In these functions individual efficiency in producing health can be proxied by education.[6] Environmental factors reflect the full cost of engaging in certain types of PA, and family structure (for instance, marital status, children) proxies for other time constraints.[7] Additional individual-level factors can be included to account for person-specific heterogeneity.

The reduced-form demand specifications for health and PA, respectively, are

$$\begin{aligned}H=H(&\text{wage}, \text{price}, \text{work PA}, \text{income}, \text{education}, \text{race},\\ &\text{ethnicity}, \text{gender}, \text{family structure}, \text{age}, \text{employment}, \text{environment factors}, \text{locational factors})\end{aligned} \quad (3)$$

$$\begin{aligned}PA_j=PA_j(&\text{wage}, \text{price}, \text{work PA}, \text{income}, \text{education}, \text{race},\\ &\text{ethnic}, \text{gender}, \text{family structure}, \text{age}, \text{employment}, \text{environment factors}, \text{locational factors})\end{aligned} \quad (4)$$

In main analyses, we estimate equation (4) for different modes of PA, denoted by the j^{th} subscript. In supplementary analyses, we also estimate equation (3) based on a self-rated measure of health.

It is assumed that individuals have greater flexibility in choosing their non-work PA relative to their work PA. That is, conditional on occupational choice, which to a large extent determines work PA, individuals then choose how to allocate their non-work time across various activities. Thus work PA also proxies for time constraints and for the full-cost of engaging in other forms of PA, and is therefore included as a potential causal determinant when estimating models for non-work PA. However, non-work PA is not assumed to have any causal effect on work PA due to the precedence of the occupational choice. It should also be noted that hours of work can vary with work PA held constant due to variations in the metabolic equivalent of the tasks performed by an individual in his or her occupation;

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[5]For convenience, the allocation of time between t_{pa} and t_{other} is ignored and the choice between t_{pa} and MET level in PA production is also ignored. However, we do present some supplementary models that separately assess effects on the duration (t_{pa}) and intensity (MET) of activities.

[6]See, for instance, Grossman (2006) who summarizes studies showing that educated individuals are more efficient at producing health.

[7]It should be noted that family structure (marriage and number of children) is also potentially simultaneously determined with career choices (and hence work-related PA). Family structure, work and career decisions, and investments in health and human capital may also be driven by unobservables such as time and risk preference, family history, and parental investments.

that is, differences in work-related PA can be due to both work hours as well as the intensity of the job. Hence, changes in wage rates can affect non-work PA through changes in hours of work. We note that the estimated effects of wage, income, and education are not sensitive to the exclusion of work PA from the specifications.

4. Data

American Time Use Surveys (ATUS)

The ATUS is the first federally-administered, continuous survey of time use in the U.S., conducted by the Bureau of Labor Statistics, with the specific objective of measuring how individuals divide up their time across all daily activities. The ATUS sample is drawn from the monthly Current Population Surveys (CPS). The CPS selects approximately 60,000 households every month from the civilian non-institutional population. About 7,500 of these households retire permanently from the CPS sample each month after their eighth CPS interview attempt. Two months after households complete their eighth CPS interview attempt, they become eligible for selection into the ATUS sample. Eligible households with a Hispanic or non-Hispanic Black householder are oversampled to improve the reliability of time-use data for these demographic groups; sampling weights are provided to yield nationally-representative estimates.

The analyses are based on the 2003–2009 waves and restricted to adults 18 years of age and older, which yields approximately 98,000 person-wave observations. Since environmental factors and locational fixed effects are potentially important determinants of PA, the sample is further restricted to individuals for whom geographic identifiers are available in the ATUS. Specifically, identifiers for metropolitan statistical areas (MSAs) are available for the approximately 60,000 individuals who reside in MSAs, and county-level identifiers are available for about 30,000 individuals who reside in large counties (with population exceeding 50,000). Data on self-reported health are only available since the 2006 wave, yielding about 29,000 observations with MSA information. Table 1 presents weighted means for all relevant variables for each of these three alternative analyses samples. There are no significant or systematic differences in the PA or other measures across these three samples, raising confidence in the comparability of the estimates across samples and their external validity.[8]

The time diary component of the ATUS interview contains a detailed accounting of the respondent’s activities, starting at 4 a.m. the previous day and ending at 4 a.m. on the interview day. Interviews are based on conversational interviewing rather than scripted questions, which is a more flexible interviewing technique designed to allow the respondent to report on his or her activities comfortably and accurately.[9] The interviewers are trained to ensure that the respondent reports activities (and durations) actually done on the previous (diary) day, not activities done on a “usual” day. Furthermore, since the focus of the questionnaire is not specifically on PA, respondents are also less likely to under-report.

[8]Strictly speaking, the estimates presented are representative of about 80% of the U.S. population that resides in MSAs.
[9]The interviewing techniques also allow interviewers to guide respondents through memory lapses, to probe in a non-leading way for the level of detail required to code activities, and to redirect respondents who are providing unnecessary information.

Gordon and Kannel (1984) contend that the quality of reports of sensitive subjects such as alcohol consumption is greatly improved if the questions are included as a small part of a much larger survey that focuses on different issues. This applies to a large scale study such as the ATUS where the focus is on time-use rather than PA per se. The ATUS has also undergone substantive field testing, cognitive research, and follow-up testing to ensure consistency of the sampling frame, minimize reporting errors, and confirm the accuracy of the responses. All cases are 100-percent verified such that two different coders cross-verify and code each case. Unlike the BRFSS and the NHIS which sample only telephone-based households, approximately five percent of the ATUS consists of CPS respondents that did not provide a telephone number in order to make the sample truly representative.

Each activity in the time diary component is assigned a six-digit classification code. The first two digits represent one of 17 major activity codes (ranging from personal care to household services to exercise and sports); the next two digits represent the second-tier level of detail, and the final two digits represent the third and most detailed level of activity. For example, the ATUS code for "making the bed" is 020101. "Making the bed" is categorized under the third-tier category 'interior cleaning', which is part of the second-tier category 'housework', which falls under the major activity category 'household activities'. Thus, unlike the national surveys used in prior studies (NHIS, BRFSS, NHANES, NMES, HRS), the ATUS does not limit the respondent to participation in a few pre-specified activities. Respondents are free to report on any activity they were engaged in, and these are meticulously coded in hundreds of categories as defined by the classification codes. For all activities, respondents report the duration in the prior 24 hours.

Dependent Variables

A total of four separate categories of non-work PA are defined with the ATUS data. These comprise: leisure PA, which captures all activities related to socializing, relaxing, and recreation including sports and exercise; active travel PA, which includes all travel related to personal care, work, and other reasons; home PA, which includes all household activities; and other PA, which includes shopping, childcare, community activities, and other non-work related activities. We also define an aggregated category for total non-work PA, which is the sum of all physical activities excluding work-related PA. Except for work PA, all of these measures of PA for all activities in the ATUS are computed by multiplying the duration of each reported activity by the metabolic equivalent of task (MET) provided by the National Cancer Institute.[10] These activities are then aggregated into the higher level categories of leisure PA, active travel PA, home PA and other PA. The MET is defined as the ratio of a person's working metabolic rate relative to their restingmetabolicrate. For example, one MET is defined as the energy it takes to sit quietly. Walking has a MET value of two, which reflects that walking expends twice the amount of energy as sitting quietly. The actual caloric expenditure for an individual in a given activity, for a given length of time, depends on the individual's bodyweight. However, caloric expenditure may not be the best measure of PA since an overweight individual would burn more calories than a lighter individual,

[10]The MET values for a large number of activities are also contained in the Compendium of Physical Activities Tracking Guide (CPA) (Ainsworth, 2002).

doing the same activity, for the same length of time. Hence, the PA measures used in this study do not include bodyweight since the higher caloric expenditure by the overweight individual does not reflect more beneficial PA but rather reflects the fact that the individual is overweight. All PA measures are defined to exclude activities which had a MET of one since the health benefits of PA extend to moderate and vigorous PA. Home PA and work PA have no activities with MET values equal to one.

The measure of work-related PA was computed based on the individual's reported occupation and reported usual time spent at work. While both usual and actual time at work are reported in the ATUS, the we ideally want to measure and control for the effect of typical work effort rather than the effect of work effort on the specific interview day. Since the diary day for about 30% of the sample was a weekend day, and since many individuals do not work on weekends, the usual time at work is more salient for computation of work-related PA. It is of interest to examine the impact of work PA on other forms of PA, and whether REG differentials in PA are mediated by work PA, due to differential sorting of individuals into various occupations. Generally, individuals who work in occupations requiring more PA participate less in leisure-time PA (MMWR, 2000). Since work PA is higher on average for Blacks and Hispanics relative to Whites, and higher for men than for women, differences in work PA may contribute to observed REG differentials in other PA and in health.

In order to compute work PA, all 502 census occupation codes[11] in the ATUS were assigned a MET value using data from the Dictionary of Occupational Titles (DOT) and the CPA.[12] The MET value for an individual's occupation was then multiplied by the individual's reported usual hours of work per day. When work PA is used as an independent variable it is, by definition, zero for individuals who are not working. A limitation of this measure is that it is derived from the individual's occupational status rather than information about the specific individual's activities at work. However, prior research has found such measures to be well-correlated with individuals' own reports of the physical demands of their jobs (Lakdawalla and Philipson, 2007).

Table 1 shows that total daily physical activity is about 27.1 MET-adjusted hours on average, which suggests that the average intensity of daily activities is about 1.12 METs. Approximately 53% of total PA consists of non-work activities (14.4 MET-adjusted hours) and about 47% constitutes work-related PA (12.7 MET-adjusted hours). Total non-work PA is comprised of leisure PA (10.1%), active-travel PA (13.7%), home PA (32.6%), and other non-work activities (43.6%).

Independent Variables

The ATUS contains extensive information on individuals' demographic and socioeconomic factors, all of which may be important determinants of PA. Indicators are defined for the

[11]ATUS occupation codes use the U.S. Census Bureau's Occupation Classification System, which is based on the Standard Occupational Classification. From 2003-10, ATUS and CPS used the U.S. Census Bureau's 2002 Occupation Classification System. These occupation codes were also used to categorize occupational affiliations as blue-collar or white-collar for all employed individuals except those in the armed forces based on the classifications in Chao and Utgoff (2003).

[12]Additional information on the computation of this variable is available from the authors.

following racial/ethnic groups: 1) non-Hispanic White (reference category); 2) non-Hispanic Black; 3) Asian; 4) other race (including American Indian, Alaskan Native, Hawaiian, and any other reported multi-racial identification; and 5) Hispanics. A dichotomous indicator is also defined for males.

A measure of total family income is constructed, representing income from all sources. Education is defined as years of formal schooling completed. Dichotomous indicators are defined for employment, part-time employment, marital status, and the presence of minor children in the household, all of which empirically proxy for time constraints. Non-linear changes in PA over the individual's life cycle are captured through linear and quadratic terms for age.

The opportunity cost of time is proxied by the wage rate for individuals who are working. Since the wage rate is not observed for those who are not employed, an interaction term is used to differentiate these individuals. This interaction term is the product of the wage rate and a dichotomous indicator for employment. Thus, for an individual who is not employed, this interaction term is equal to zero and for an individual who is employed, the interaction term is equal to the wage rate. This ensures that the wage effect is identified only from changes in the observed wage rate across employed individuals. This does not assume that the value of time is zero for people who do not work. Instead, it assumes that the regression coefficients of determinants other than the wage are the same for those not employed and for the employed. Empirically, our main results are very similar when we restrict our regressions to those who are employed.[13] All monetary variables are deflated by the national consumer price index.

Appended Data

The full cost of engaging in PA is also related to environmental characteristics including population density, weather and crime rates. High crime rates, temperature extremes, and high levels of precipitation can raise the full price of engaging in PA in such neighborhoods, by making outdoor activities dangerous or more difficult, and thereby reduce PA. Low population density could increase driving (relative to walking or bicycling) but may also reflect more recreational options. Zhao and Kaestner (2010), for instance, find that population density is negatively related to obesity.

Information on recreational equipment rental stores per capita, pedestrian fatalities per capita, crimes per capita, population density, and weather is linked to the individual records in the ATUS based on the respondent's county of residence and time of interview. Identification of the county of residence is available for about 30,000 individuals who reside in large counties with a population over 50,000 individuals.[14] Information on the number of establishments for fitness and recreational sports centers is obtained from the U.S. Census County Business Patterns.[15] Pedestrian fatalities are obtained from the Fatal Accident

[13]We lack variables to plausibly identify and estimate a sample selection model. Without such exclusion restrictions, the selection model would be identified purely from the functional form, which is not plausible. We treat work PA in the same manner as we treat the wage in the non-work PA regressions.
[14]Appended county level variables for 2009 were not yet available.
[15]See: www.census.gov/epcd/cbp/view/cbpview.html

Reporting System (FARS). Crime is proxied by arrest rates for all crime, property crime, and violent crime, derived from the Federal Bureau of Investigation's Uniform Crime Reports. Data on average daily temperature, average annual precipitation, and population density are obtained at the county-month level from Fedstats.[16] Non-linear effects of temperature are captured through a quadratic term. The Area Resource File (ARF) provides information on population density per square mile for all counties in the U.S.

Fixed Effects

Alternate models include locational fixed effects (MSA and county), which control for all time-invariant unobserved area-specific factors. These fixed effects also account for the individual's built environment, including sidewalks, presence of open spaces and parks, biking trails, public transportation, traffic, and other neighborhood attributes, to the extent that these have remained relatively unchanged in the individual's MSA or county of residence between 2003 and 2009. Time fixed effects (month and year), included in all models, account for seasonal factors and national trends affecting PA as well as overall changes in the cost-of-living over time. Standard errors are adjusted for arbitrary correlation across individuals residing within the same MSA and residing within the same county (for models that exploit information on county of residence) for each month and year.

5. Results

REG Differentials

Table 2 presents multivariate models for six categories of PA – leisure, active travel, home, other non-work, total non-work, and work. The unadjusted specification represents the baseline model, which includes only the REG variables and time (month and year) fixed effects. The coefficients of the REG variables in this baseline specification are interpreted as observed or unconditional REG differentials. The adjusted model is based on equation (4) and provides a conditional measure of REG differentials by controlling for the influence of observable individual heterogeneity (other than race, ethnicity or gender). On a given day, individuals have greater choice over their non-work PA relative to their activities at work, since work activities are primarily determined by the occupation. Therefore, work PA is included as a determinant of leisure PA and all other types of non-work PA in the extended specification. Measures of the individual's age, human capital, family structure, employment status, wage and non-wage income, marital status, and locational choice, the latter captured by fixed effects for MSA of residence, are also included in the adjusted model. Thus, a comparison of the REG coefficients between the unadjusted and adjusted specifications can inform how much of the observed REG differentials in PA are associated with observable person-specific factors and how large are the REG differentials after conditioning on these observables.

The estimated coefficients on REG for leisure PA are shown in columns (1) and (2) for the unadjusted and adjusted models, respectively. Blacks and Hispanics have significantly lower leisure PA relative to non-Hispanic Whites, by about 0.54 and 0.27 MET*hours,

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[16]See: www.fedstats.gov

representing about 37% and 18% reduction relative to the mean. Including the additional person-specific factors and MSA fixed effects reduces the differential for Blacks (by about a third), but does not meaningfully affect the differential for Hispanics. This suggests that some of the Black-White differential for leisure PA is driven by observed heterogeneity in human capital and other factors, though even after controlling for these factors a significant differential persists. We also find that Asians have a significantly lower level of leisure PA, after controlling for the extended factors, by about 0.4 MET*hours (about 27% relative to the mean).

A similar pattern is observed for other categories of PA shown in columns (3) through (8). Blacks and Hispanics have lower active-travel and home PA relative to non-Hispanic Whites, but after adjusting for additional factors, the differentials are diminished. Indeed, the coefficient for Hispanics is not significantly different from (non-Hispanic) Whites in the extended specification. This suggests that the Hispanic-White differential for active travel and home PA can be attributed entirely to differences in observed heterogeneity. For other non-work PA, including additional covariates reduces the gap by 33% and 46% among Blacks and Hispanics, respectively.

Columns (9) through (12) present models for the aggregated category of total non-work PA, and for total work PA. Unadjusted differentials suggest that, on average, non-work PA is significantly lower among Blacks (by 3.7 MET*hours or 26%) and Hispanics (1.4 MET*hours or 10%) relative to non-Hispanic Whites. While significant differences persist in the extended specifications, these gaps are reduced by 29% (for Blacks) and 57% (for Hispanics).[17] Differentials for expectedly work-related PA are in the opposite direction. Among employed persons, column (11) shows that total work PA is significantly higher among Blacks (by 1.9 MET*hours or 9%) and among Hispanics (by 3.1 MET*hours or 15%), consistent with these individuals being more likely to work in blue-collar and physically demanding occupations in the construction, manufacturing, and agriculture sectors. Thus, accounting for observable factors such as education and location substantially diminishes this gap (by 59–65%).

For Blacks and other racial groups, higher levels of work PA relative to non-Hispanic Whites is counteracted by lower levels of non-work PA. Among Asians, however, both types of PA are lower. Specifically, work-related PA is less relative to non-Hispanic Whites (by about 9%), and this gap diminishes by almost a half when conditioning on human capital and other person-specific characteristics. Non-work PA is also significantly less among Asians, by about 9%, after controlling for observables. This latter gap actually becomes wider, after controlling for the observables, mostly due to the positive effects of education and other income on non-work PA, both of which are higher among Asians relative to non-Hispanic Whites.

Next we examine gender differences across the various PA categories. Males have significantly higher levels of leisure PA (1.0 MET*hours or 70% relative to the mean) and

[17]The exception is for Asians, where the differential in leisure, active-travel PA, and total non-work PA increase in the adjusted model. This may be due to higher income and education-levels among Asians, which tend to raise leisure and active travel PA. In addition, Asians have lower work PA which tends to lower leisure, active travel PA, and total non-work PA in general.

active travel PA compared to females. This is consistent with Rombaldi et al. (2010) who also find that leisure PA and active travel PA are likely to co-occur. By contrast, men have lower home PA (1.7 MET*hours or 34% relative to the mean) and other non-work PA. Men have higher work PA (6.2 MET*hours or 31% relative to the mean) relative to women. In comparison with the race/ethnicity differentials, observable human capital and other factors are able to explain a relatively smaller portion of the unadjusted gender differentials, on the order of 14–37%.

In supplementary models[18], we also separately consider REG effects on the duration of leisure-time PA (total number of hours engaged) and intensity (average MET value in leisure PA for each individual). The directions of these differentials are generally consistent with those reported for total leisure PA (MET*hours). Specifically, we find that Asians, Blacks, Hispanics, and other races have a significantly lower duration as well as a lower intensity of leisure PA, relative to non-Hispanic Whites. With respect to the intensity of leisure PA, the observed human capital, socioeconomic factors, and MSA fixed effects can account for about 43%–61% of the observed differential among Blacks and Hispanics, respectively. With respect to duration, these factors account for a relatively smaller portion of the differential, on the order of 25–31%. In addition, work PA significantly reduces both the duration and intensity of leisure PA. The gender differential in the duration and intensity of leisure PA remains fully robust in both the adjusted and unadjusted models, suggesting that the observed person-specific characteristics are not driving the higher leisure PA among males.

Other Factors

Table 3 presents the estimates of the additional covariates, which were included in the adjusted model but not reported in Table 2. The coefficients of the age terms are interpreted as an indication of how PA shifts over the lifecycle. Total non-work and work-related PA generally increase into the late-30s and early-40s but then decline with age. Home PA increases into the mid-50s and then declines. Leisure PA, on the other hand, exhibits a convex relationship over the life cycle, declining into the 60s but then increasing. This late rise in leisure PA is reflective of a lower opportunity cost of time and higher time endowment post-retirement, and may also reflect that the older respondents in the sample may be of better health and thus more likely to be physically active.[19]

We separately model the effect of income based on wage and non-wage income. Wage income reflects the hourly wage rate computed as weekly earnings divided by the usual hours worked per week. This measure captures the opportunity cost of time for non-work PA. Wage is negative associated with work PA which suggests that higher wage individuals work in less physically-demanding occupations. The result is not prima facie consistent with models of compensating wage differentials, which suggest that more physically-demanding occupations must offer higher wage rates to induce workers to enter them. This, however,

[18]Results are not reported, and are available upon request.
[19]This is not to say that an hour at age 70 is the same as an hour at age 20 in terms of intensity. Indeed, when we separate out the effects of the life cycle on duration and intensity, the inflection in the age-profile for intensity occurs slightly earlier, at around the age of 61, whereas the inflection for duration occurs around mid-to-late 60s.

may be due to incomplete measures of human capital included in the model or to imperfect markets for human capital. The negative effect of the wage rate on work PA is further reflecting a cross-occupation effect, rather than changes in energy demand within occupational categories.

The wage rate is positively associated with all other forms of PA (though the effect of home PA is statistically insignificant). At first blush, the positive wage effect may seem puzzling with other non-wage income being held constant. Hence, an increase in the wage might be expected to increase hours of work and reduce leisure PA through a pure substitution effect. However, an increase in the wage also raises the marginal monetary rate of return on an investment in health and therefore the optimal quantity of health in Grossman's (1972) pure investment framework. The demand for time used in the production of health rises if the output effect outweighs the substitution in production effect. Given that work PA is being held constant, which partly captures the duration of work (in addition to intensity), it is likely that the wage effect is reflecting this output effect from an increase in the underlying demand for health. Alternatively, higher wage individuals may also exercise more intensely (Meltzer and Jena 2010), leading to an increase in leisure PA.

Other income captures family income, excluding the individual's wage income, and is interpreted as a wealth effect. As expected, other income is negatively associated with work PA and positively associated with leisure PA. Somewhat puzzling is that other income is positively associated with home PA. This may reflect sorting between home and work PA across household members, particular if there is sufficient wage income from others in the household. This also explains why the wage income is not significantly associated with home PA.

Consistent with wage income, education is negatively associated with work PA suggesting that more educated individuals work in less physically demanding occupations. However, unlike wage income, education is not significantly associated with leisure PA. This suggests that education does not have a direct effect on leisure PA but rather has an indirect effect through higher wages and through work PA.

Employment and PA at work are expectedly associated with significantly lower leisure and home PA. The exception is active travel PA which is positively associated with employment. This suggests some complementarity between active travel PA and employment, which may reflect commuting to work; thus, consistent with a dose-response relationship, part-time workers engage less than full-time workers. Not only does employment reduce leisure PA, work PA also crowds out leisure PA, consistent with a substitution between work and non-work PA, though the crowd-out is far less than one-to-one. Interestingly, part-time workers also have lower leisure PA relative to full-time workers which suggests that part-time status does not reflect greater leisure activities.

Married individuals are less engaged in leisure and active travel PA, reflecting the higher full cost of PA due to greater time constraints. They are engaged in more home and work PA. A greater number of children in the household increases total non-work PA, particularly home PA and other non-work PA as expected, but does not have any discernible effect on work PA or leisure PA.

REG Differentials by Subgroups

Table 4 presents adjusted REG differentials in leisure PA separately by various subgroups, based on educational attainment, blue-collar work, and self-rated health status. Due to limited sample sizes and potentially endogenous stratification, the estimates should be interpreted with caution. Nevertheless, these estimates further inform whether the REG disparities reported in Table 3 are different across these groups. Stratifying across these characteristics may also lead to more homogeneous samples that are balanced on unobservable confounding factors; for instance, lower-educational attainment may be associated with a high rate of time preference which would also be correlated with health investments such as physical activity.

As shown in columns (1) and (2), REG differentials persist even among those with college degrees and above as well as those with less than a college degree. This is consistent with earlier results from Table 3 which suggested that education did not have a statistically significant effect on leisure PA. Columns (3) and (4) show REG differentials by occupation type. Among white collar workers, all racial groups engage in less leisure PA, relative to non-Hispanic Whites, though the differential for Hispanics (on the order of 10%) and other races (40%) imprecisely estimated. Among blue collar workers, significant REG differentials persist among all groups with the exception of other races.

One concern is that the association between REG and physical activity may be driven by health disparities, though the causal link between physical activity and health may run in both directions. Columns (5) and (6) therefore show REG differentials by stratifying on self-rated health. Among those reporting excellent or very good health, approximately 54% of the sample, we find that Asians, Blacks, and Hispanics engage in lower levels of leisure PA relative to the reference group of non-Hispanic Whites, whereas males engage in higher levels of leisure PA relative to females. These directions of effects are similar to those reported for the pooled sample in Table 2, suggesting that REG differentials in leisure PA are not driven fully by differences in health status.[20] Among those in fair or poor health, which is only about 16% of the sample, there are no significant differences among Asians and Blacks, relative to non-Hispanic Whites, whereas Hispanic are have a significantly higher level of leisure PA. The small sample size for this group warrants caution, though these results suggest that at least among those on the lower tail of the health distribution there are no significant racial differences in leisure PA. The gender difference persists.

Self-rated Health

Table 5 presents estimates for specifications which use self-reported health as the dependent variable. Health is measured here as a dichotomous indicator capturing individuals who

[20]We also estimated models for total non-work and work PA for individuals reporting excellent or very good health. The results are robust and the REG differentials follow the same patterns as noted in Table 2 for the pooled sample. Hence, at least among the majority of individuals who are healthy, the REG differences persist and are not fully explained away by differences in health driving the association between REG measures and PA.

report that their health is excellent or very good. These models are estimated via probit regression, and marginal effects are presented. Column 1 shows that all racial/ethnic groups have a lower probability of reporting excellent or very good health by between 5–22 percentage points, relative to non-Hispanic Whites. Males have a two percentage point higher probability of reporting excellent or very good health relative to females.

Column 2 adds controls for age, education, family structure, employment, income and wages, and MSA fixed effects. Comparing columns 1 and 2, about 43–48% of the observed health differential for Blacks and Hispanics can be attributed to these factors. However, the inclusion of these factors causes the gender differential to reverse; males are now less likely to be in excellent or very good health by about 1.3 percentage points. Racial/ethnic differentials in health persist even after accounting for these individual-level human capital, socioeconomic factors, and residential choice.

Since non-work PA is associated with better health, REG differentials in PA may potentially contribute to REG differential in health. Column (3) investigates this possibility by controlling for work PA and total non-work PA.[21] It should be noted that since PA and health are endogenous these coefficients should not be interpreted as causal. The PA measures act as controls and thus their coefficients can be interpreted as partial correlations. The coefficients in column (3) can differ from those of column (2) to the extent that the PA measures are correlated with the individual-specific characteristics, and to the extent that endogeneity bias has been introduced into the equation. The robustness of the other non-REG coefficients between columns (2) and (3) suggests that any endogeneity bias introduced by the PA measures does not significantly impact the conclusions derived from the estimates in column (3), at least with respect to direction and significance. Nevertheless, due to the potential endogeneity between PA and health, the marginal effects of PA in column (3) are meant to be suggestive of partial correlations and should not be interpreted as measures of causal influence.

Work PA and total non-work PA does not substantially contribute to the observed health differential among Hispanics, Asians, or other racial groups. However, among males, it can potentially account for 26% of the observed health differential (though the absolute health differential across genders is relatively small).

The magnitude of the non-work PA effect is of interest. The variable has a mean of 14.4 and a standard deviation of 9.4 MET*hours. Hence a one-standard deviation increase in non-work PA is associated with a 4.0 percentage points (7.4% relative to the mean) increase in the probability of being in excellent or very good health. This is somewhat larger than the 2.8 percentage points increase in the probability of being in excellent or very good health associated with a one-year increase in formal schooling. This increase in schooling, however, only amounts to about a third of its standard deviation. Clearly, a full evaluation of alternative policies to improve health by expanding non-work PA on the one hand and

[21]While specification 2 is a reduced-form health demand function, specification 3 is a mixture of a demand function and a production function since work and non-work PA are inputs into the production of health.

schooling on the other hand requires refined estimates of the causal nature of these associations that we have reported and information on the costs of each policy.

The causality from total non-work PA to health and from health to total non-work PA is theorized to be positive in both directions. The positive and significant coefficient of total non-work PA most likely reflects that these two underlying relationships are both positive. However, in the case of work PA, prior studies suggest that work PA may potentially have an adverse impact on health (at least for some physically-demanding occupations with high and sustained energy requirements), but health tends to have a positive effect on work PA. In column 3, the coefficient of work PA is insignificant which may reflect that these two underlying relationships are oppositely signed.

Table 6 presents the probit models for health separately by subgroups based on education and occupation status. Among those with a college degree or more (column 2), both work and non-work PA are positively associated with health. However, among those with less than a college degree (column 1) the effect of work PA is insignificant. This suggests that among high-skilled labor, both work and non-work PA may have positive effects on health, whereas for low-skilled labor, the effects of work PA may be muted and even possibly detrimental due to the persistently high energy demands of certain occupations in construction or manufacturing (Kukkonen-Harjula 2007). Columns (3) and (4) confirm these effects across occupation type. Specifically, among blue and white-collar workers, non-work PA is positively associated with health, whereas there is no significant link between work PA and the health of blue-collar workers.

Geographical factors

Table 7 assesses the effects of various geographical-level attributes on leisure PA. Column (1) represents the adjusted model for the sample of individuals who reside in large counties and for whom information on residential county is available. Although the sample size is only about 40% of the MSA sample, the REG differentials are highly similar, suggesting that there are no substantial sample selection issues and that the estimates are comparable across samples. The county-level environmental factors are potentially endogenous if individuals who have a preference for leisure PA choose to live in locations which are more conducive to these activities. The degree of this endogeneity of location to career choice and other unobservable life decisions may vary across racial and ethnic groups due to residential segregation, and further confound REG differentials. With the exception of population density and temperature (both positively affecting PA), the other environmental measures are not significant. This is due to the inclusion of county-level fixed effects, which may already be capturing much of the variation in environmental attributes across localities.

Column (2) in Table 7 shows the mean estimated MSA fixed effects by census division (Northeast, Midwest, South, and West). These estimates confirm the existence of some regional differences in leisure PA engagement. Specifically, individuals residing in the West had the highest average daily levels of leisure PA, whereas leisure PA in the other three regions is fairly similar. The differences between the West and the other three regions are statistically significant.[22]

There may also be a social aspect to certain types of leisure-time activities, for instance relating to exercising or recreation. The model in column (3) partly accounts for this aspect by controlling for the mean leisure PA participation rate (excluding the individual) in the individual's MSA and race/ethnic/gender group.[23] The caveat regarding unobserved MSA-level confounding factors notwithstanding, this measure would crudely capture the possibility that a respondent's leisure-time PA would be higher if other similar (based on race/ethnicity/gender) individuals in their area of residence and time period are also relatively active. The estimated impact of the MSA-REG leisure PA participation rate on the individual's own leisure PA is significantly positive. Specifically, a 10% increase in the participation rate is associated with a 0.112 MET*Hours increase in leisure PA (approximately 7.6% increase relative to the mean). Nevertheless, the inclusion of this control does not materially affect the REG differentials, which remain robust for Blacks, Hispanics, Asians, and males.

6. Conclusions

There is a fundamental two-way connection between health and knowledge-based human capital. Education has been found to make individuals more allocatively and technically efficient in producing health capital (see for instance Grossman 2006), and health also contributes to the accumulation of human capital. Poor health in childhood, for instance, can have durable effects on human capital acquisition through formal education as well as other channels, and such adverse health effects can lead to an inter-generational transmission of income and well-being (Ehrlich and Lui 1991). Hence, understanding disparities in health inputs, such as physical activity, can shed light on persistent disparities in health and human capital.

This study utilizes all-inclusive measures of PA from a nationally-representative sample, which capture both the duration and intensity of all activities, to assess REG differentials and the extent to which these differentials are mediated by observable human capital and socioeconomic factors. Estimates indicate that leisure PA comprises only about 10% of total non-work PA. This underscores the importance of considering all types of PA since an exclusive focus on a single type of PA can substantially understate activity levels and lead to biased estimates of REG differentials. Estimates suggest that non-work PA is significantly lower among Blacks, Hispanics, other racial groups as well as among males. These differentials can be partially explained by education, socioeconomic status, proxies for time constraints, and locational fixed effects. Observed differentials in non-work PA among Blacks, Hispanics, and males diminish by between 29–57% after accounting for individual-level human capital, work PA, other socioeconomic factors, and locational choice. Work PA is significantly lower among Asians and higher among all other racial/ethnic groups relative to non-Hispanic Whites. It is also significantly higher among males. Observed human capital and socio-economic characteristics can account for about 50–65% of the observed

[22]Expectedly, estimating the same specification with region indicators (in lieu of the MSA indicators) yields virtually identical results.

[23]Note that it would not be appropriate to include the mean level of leisure PA by MSA/REG groups since, by definition, the coefficient on group means will be one if defined from the same dataset.

race/ethnicity differential in work PA among employed individuals and about 23% of the observed gender differential.

Results further suggest that work PA significantly crowds out non-work PA. Thus, to the extent that lower-educated individuals and minority racial/ethnic groups tend to have higher levels of work PA but lower levels of non-work PA, this shift in the composition of physical activity may diminish the positive effects of PA on health since non-work PA is found to have a stronger positive association with health relative to work PA. We specifically find this to be the case among low-educated individuals and among those working in blue-collar occupations.

A number of studies have investigated education, health behaviors, and access to medical care as factors contributing to REG differences in health. However, PA remains an understudied factor as a potential contributor to these health differences. This study shows that significant REG differentials in work PA and non-work PA exist. And, whereas about a third to half of these differences can be attributed to human capital, time constraints, and locational choices, a substantial differential persists even after controlling for these factors. Since non-work PA, in particular, is associated with better mental and physical health outcomes, reducing the disparities in PA may contribute towards narrowing the REG health gradient. Given the inherent link between health capital and knowledge-based human capital, REG-related variance in PA may also play a role in the accumulation of human capital either through schooling, on-the-job training, or work-related experience. Future research should focus on disentangling the causal link between physical activity (and the composition of PA across different modes and across duration and intensity) and health, which can shed further light on the extent to which the observed differences in these various modes of work and non-work PA can help to explain persistent REG disparities in morbidity and mortality.

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Table 1

Sample-weighted Means

Variable Name	ATUS Variables Definition	MSA Residents	MSA Residents with Health Data	Large County Residents
Total PA	Total PA in all activities (hours times MET)	27.109	27.334	27.264
Leisure PA	Leisure PA (hours times MET).	1.463	1.474	1.523
Active travel PA	Active Travel PA (hours times MET).	1.969	1.952	1.992
Home PA	Home PA (hours times MET).	4.698	4.688	4.702
Other PA	PA in all other non-work Activity (hours times MET).	6.289	6.25	6.312
Total non-work PA	Total Non-work PA (hours times MET).	14.419	14.364	14.529
Work PA	Work PA (usual work hours times MET).	12.69	12.979	12.735
Work PA (employed only)	Work PA (usual work hours times MET). n = 37,696.	20.173	20.356	20.206
White	Equals one if the individual is White.	0.661	0.655	0.619
Asian	Equals one if the individual is Asian.	0.037	0.039	0.046
Black	Equals one if the individual is Black.	0.122	0.121	0.117
Hispanic	Equals one if the individual is Hispanic.	0.162	0.165	0.199
Other Race	Equals one if the individual is American Indian, Alaska Native, Hawaiian or reports any race combination.	0.017	0.02	0.019
Male	Equals one if the individual is Male.	0.474	0.477	0.472
Age	Age of individual.	42.681	42.721	42.219
Education	Years of education.	13.31	13.348	13.27
Employed	Equals one if the individual is employed.	0.63	0.638	0.631
Part-time	Equals one if the individual is employed part-time	0.127	0.124	0.128
Blue Collar	Equals one if manual labor occupation	0.228	0.233	0.227
White Collar	Equals one if non-manual labor occupation	0.402	0.405	0.403
Wage	Hourly wage rate times employed. Zero for individuals who are not employed.	12.427	12.945	12.304
Other Income	Weekly family income minus weekly wage income or zero if difference is negative. (per 1000 dollars)	0.712	0.738	0.696
Married	Equals one if the individual is married.	0.528	0.529	0.524
Children	Number of children in the household under 18.	0.848	0.848	0.87
Health	Equals one if the individual reports that their health is either excellent or very good.		0.539	
Appended Variables 2003–2008				
Crime	Per capita crimes per year.			39.921
Pedestrian Fatalities	Per capita pedestrian fatalities per year.			0.018
Temperature	Average daily temperature.*			58.589
Temperature Squared	Average daily temperature squared.*			3676.49
Precipitation	Average daily precipitation.*			2.93
Sports rental	Per capita number of stores that rent recreational equipment.			0.005

Variable Name	ATUS Variables Definition	MSA Residents	MSA Residents with Health Data	Large County Residents
Population Density	Population per square mile.			3079.127
Data Period		2003–2009	2006–2008	2003–2008
Sample size		60,424	22,963	23,746

* Monthly and county variation but no annual variation

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Table 2

(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Active Travel PA		Home PA		Other Non-work PA		Total Non-work PA		Total Work PA	
justed	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
*** (0.101)	−0.0828* (0.0467)	−0.297*** (0.0473)	−0.856*** (0.127)	−0.648*** (0.127)	0.941*** (0.144)	0.0637 (0.138)	−0.128 (0.202)	−1.272*** (0.199)	−1.922*** (0.225)	−0.908*** (0.209)
*** (0.0557)	−0.183*** (0.0264)	−0.103*** (0.0278)	−1.882*** (0.0703)	−1.565*** (0.0769)	−1.126*** (0.0667)	−0.609*** (0.0695)	−3.730*** (0.111)	−2.636*** (0.117)	1.870*** (0.148)	0.770*** (0.140)
*** (0.0666)	−0.146*** (0.0253)	0.0413 (0.0302)	−0.230*** (0.0772)	0.138 (0.0867)	−0.759*** (0.0645)	−0.512*** (0.0775)	−1.409*** (0.108)	−0.604*** (0.127)	3.080*** (0.135)	1.071*** (0.147)
0 (0.187)	−0.189*** (0.0704)	−0.116* (0.0691)	−0.786*** (0.209)	−0.372* (0.208)	0.171 (0.191)	−0.0300 (0.186)	−0.878*** (0.325)	−0.748** (0.318)	0.686* (0.367)	0.163 (0.325)
** (0.0456)	0.544*** (0.0186)	0.452*** (0.0193)	−1.691*** (0.0556)	−1.453*** (0.0574)	−1.666*** (0.0464)	−1.252*** (0.0479)	−1.791*** (0.0796)	−1.136*** (0.0829)	6.226*** (0.0929)	4.769*** (0.0886)
0,424	60,424	60,424	60,424	60,424	60,424	60,424	60,424	60,424	37,665	37,665
0.045	0.017	0.078	0.027	0.085	0.028	0.127	0.029	0.103	0.125	0.345

lation within MSA-year month cells, are reported in parentheses.

month and year. Adjusted model includes variables for age, age squared, education, employed, part-time employment, work PA, family income, wage,
cators. Models for Total Work PA in columns (11) and (12) are restricted to the sample of employed individuals, and excludes variables for employed and

Table 3

Determinants of PA

VARIABLES	(1) Leisure PA	(2) Active Travel PA	(3) Home PA	(4) Other Non-work PA	(5) Total Non-work PA	(6) Total Work PA
Age	−0.0867*** (0.00670)	0.0496*** (0.00287)	0.310*** (0.00853)	−0.160*** (0.00786)	0.112*** (0.0128)	0.342*** (0.0187)
Age Squared	0.000630*** (6.41e-05)	−0.000540*** (2.93e-05)	−0.00274*** (9.11e-05)	0.00110*** (7.98e-05)	−0.00155*** (0.000132)	−0.00400*** (0.000211)
Education	0.0106 (0.00766)	0.0727*** (0.00344)	−0.0131 (0.0100)	0.254*** (0.00842)	0.324*** (0.0144)	−0.579*** (0.0220)
Employed	−0.185* (0.0975)	0.564*** (0.0434)	−1.792*** (0.128)	−1.549*** (0.106)	−2.963*** (0.188)	
Part-time	−0.131* (0.0685)	−0.156*** (0.0330)	0.476*** (0.0940)	0.839*** (0.0849)	1.028*** (0.137)	−9.132*** (0.0943)
Work PA	−0.0153*** (0.00319)	0.000552 (0.00146)	0.00571 (0.00461)	−0.0319*** (0.00340)	−0.0409*** (0.00648)	
Wage	0.0148*** (0.00245)	0.00289*** (0.000836)	0.00289 (0.00190)	0.00420** (0.00168)	0.0248*** (0.00370)	−0.0725*** (0.00811)
Other Income	0.497*** (0.0400)	0.0743*** (0.0157)	0.189*** (0.0457)	0.360*** (0.0430)	1.121*** (0.0682)	−1.167*** (0.0855)
Married	−0.328*** (0.0420)	−0.161*** (0.0209)	0.813*** (0.0621)	0.529*** (0.0521)	0.853*** (0.0872)	0.469*** (0.100)
Children	0.00643 (0.0207)	0.0720*** (0.00914)	0.250*** (0.0262)	0.590*** (0.0237)	0.918*** (0.0384)	−0.0150 (0.0409)
Observations	60,424	60,424	60,424	60,424	60,424	37,665
R-squared	0.045	0.078	0.085	0.127	0.103	0.345

Notes: Standard errors, adjusted for arbitrary correlation within MSA-year-month cells, are reported in parentheses.

Asterisks denote statistical significance as follows:

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

All models include MSA, month, and year indicators. Race, ethnicity, and gender parameter estimates are not shown (they are reported in Table 2). The model for Total Work PA is restricted to the sample of employed individuals.

Table 4

Leisure PA: REG Differentials by subgroups

	(1)	(2)	(3)	(4)	(5)	(6)
	Leisure PA					
VARIABLES	Less than college	College or more	Blue Collar	White Collar	Excellent/Very Good Health	Fair/Poor Health
Asian	−0.349* (0.181)	−0.547*** (0.126)	−0.602*** (0.228)	−0.496*** (0.130)	−0.888*** (0.198)	0.108 (0.276)
Black	−0.254*** (0.0664)	−0.566*** (0.0991)	−0.380*** (0.126)	−0.431*** (0.0791)	−0.188 (0.164)	−0.0140 (0.126)
Hispanic	−0.307*** (0.0787)	−0.457*** (0.134)	−0.452*** (0.129)	−0.139 (0.104)	−0.337* (0.182)	0.456** (0.182)
Other Race	−0.305 (0.197)	0.112 (0.478)	−0.566 (0.348)	−0.392 (0.272)	0.235 (0.644)	0.197 (0.280)
Male	1.188*** (0.0571)	0.848*** (0.0745)	0.877*** (0.0944)	0.908*** (0.0676)	1.366*** (0.115)	0.692*** (0.129)
Observations	40,983	19,441	12,090	25,606	12,399	3,679
R-squared	0.059	0.040	0.058	0.040	0.062	0.094
p-value†						
Asian	0.3707		0.6818		0.0022	
Black	0.0081		0.7308		0.3893	
Hispanic	0.3264		0.0540		0.0014	
Male	0.0003		0.7877		0.0001	

Notes: Standard errors, adjusted for arbitrary correlation within MSA-year-month cells, are reported in parentheses.

Asterisks denote statistical significance as follows:

*** p<0.01,

** p<0.05,

* p<0.1.

All models include variables for age, age squared, education, employed, part-time employment, work PA, family income, wage, married, children, and MSA, month, and year indicators.

† T-test for whether estimated coefficients for Asian, Black, and Hispanic are different across the stratified

Table 5

Self-rated Health: Probit models

	(1)	(2)	(3)
VARIABLES	Excellent/Very Good Self-rated Health		
Asian	−0.0525*** (0.0173)	−0.142*** (0.0172)	−0.136*** (0.0171)
Black	−0.172*** (0.00963)	−0.0900*** (0.00994)	−0.0804*** (0.00992)
Hispanic	−0.220*** (0.00854)	−0.126*** (0.0102)	−0.124*** (0.0101)
Other Race	−0.0990*** (0.0233)	−0.0860*** (0.0225)	−0.0857*** (0.0225)
Male	0.0169*** (0.00641)	−0.0125** (0.00634)	−0.00926 (0.00652)
Age		−0.0121*** (0.00106)	−0.0126*** (0.00105)
Age Squared		8.47e-05*** (1.11e-05)	9.10e-05*** (1.10e-05)
Education		0.0292*** (0.00128)	0.0279*** (0.00128)
Employed		0.111*** (0.0106)	0.116*** (0.0158)
Part-time		−0.0478*** (0.0106)	−0.0487*** (0.0117)
Wage		0.00233*** (0.000371)	0.00223*** (0.000365)
Other Income		0.0941*** (0.00530)	0.0900*** (0.00530)
Married		0.0121* (0.00720)	0.00862 (0.00720)
Children		−0.000295 (0.00316)	−0.00416 (0.00316)
Work PA			0.000572 (0.000482)
Total Non-work PA			0.00421*** (0.000342)
Observations	22,963	22,963	22,963
Pseudo R-squared	0.0256	0.118	0.123

Notes: Standard errors, adjusted for arbitrary correlation within MSA-year-month cells, are reported in parentheses.

Asterisks denote statistical significance as follows:

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

All models include MSA, month, and year indicators.

Table 6

Self-rated Health: Probit models by subgroups

	(1)	(2)	(3)	(4)
	Excellent/Very Good Self-rated Health			
VARIABLES	**Less than college**	**College or more**	**Blue Collar**	**White Collar**
Asian	−0.104*** (0.0273)	−0.157*** (0.0209)	−0.105** (0.0502)	−0.165*** (0.0220)
Black	−0.0704*** (0.0115)	−0.103*** (0.0186)	−0.0726*** (0.0216)	−0.0997*** (0.0156)
Hispanic	−0.131*** (0.0121)	−0.0926*** (0.0210)	−0.182*** (0.0201)	−0.0811*** (0.0167)
Other Race	−0.0610** (0.0266)	−0.154*** (0.0417)	−0.0757 (0.0548)	−0.125*** (0.0349)
Male	0.00994 (0.00824)	−0.0462*** (0.0111)	0.0339** (0.0158)	−0.0132 (0.0102)
Total Non-work PA	0.00429*** (0.000416)	0.00391*** (0.000592)	0.00162** (0.000769)	0.00223*** (0.000541)
Work PA	−7.14e-05 (0.000595)	0.00220** (0.000877)	0.000536 (0.000900)	0.00179** (0.000789)
Observations	15,458	7,434	4,601	9,741
Pseudo R-squared	0.105	0.0843	0.106	0.0672
p-value†				
Asian	0.0490		0.2326	
Black	0.0597		0.2468	
Hispanic	0.3005		0.0003	
Male	0.0000		0.0124	

Notes: Standard errors, adjusted for arbitrary correlation within MSA-year-month cells, are reported in parentheses.

Asterisks denote statistical significance as follows:

*** p<0.01,

** p<0.05,

* p<0.1.

All models include variables for age, age squared, education, employed, part-time employment, work PA, family income, wage, married, children, and MSA, month, and year indicators.

† T-test for whether estimated coefficients for Asian, Black, and Hispanic are different between stratified samples.

Table 7

Leisure PA: Geographical attributes

	(1)	(2)	(3)
VARIABLES		**Leisure PA**	
Asian	−0.273 (0.167)	−0.391*** (0.101)	−0.359*** (0.0985)
Black	−0.341*** (0.0936)	−0.360*** (0.0557)	−0.344*** (0.0565)
Hispanic	−0.223** (0.103)	−0.271*** (0.0666)	−0.163*** (0.0599)
Other Race	−0.387 (0.257)	−0.230 (0.187)	−0.143 (0.190)
Male	1.155*** (0.0719)	1.117*** (0.0456)	1.069*** (0.0470)
MSA-race-gender-specific LPA participation rates			1.120*** (0.299)
Crime	0.0139 (0.0105)		
Pedestrian Fatalities	7.794 (6.110)		
Sports Rental	−0.927 (18.96)		
Population Density	0.000738** (0.000337)		
Temperature	0.0328** (0.0138)		
Temperature Squared	−0.000109 (0.000162)		
Precipitation	−0.0143 (0.0306)		
Observations	23,746	60,424	60,424
R-squared	0.056	0.123	0.040
County FE	Y	N	N
MSA FE:	N	Y	N
Predicted LPA by region†			
Northeast		1.345*** (0.0437)	
Midwest		1.366*** (0.0407)	
South		1.381*** (0.0329)	
West		1.567*** (0.0437)	
p-values‡			
Northeast=Midwest		0.726	
Northeast=South		0.503	
Northeast=West		0.000333	
Midwest=South		0.762	
Midwest=West		0.000908	
South=West		0.000702	

Notes: Standard errors, adjusted for arbitrary correlation within MSA-year-month cells, are reported in parentheses.

Asterisks denote statistical significance as follows:

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$.

All models include variables for age, age squared, education, employed, part-time employment, work PA, family income, wage, married, children, and MSA, month, and year indicators. Leisure PA participation rate is calculated as the sample-weighted leisure participation rate for each race/ethnicity by gender group in an MSA (excluding the own respondent). Northeast, Midwest, South, and West are based on census regional divisions.

†Estimates are the predicted LPA grouped by census regions using the observed MSA indicators at the mean values for all other variables.

‡Wald tests for whether the predicted LPA estimates by region are statistically different are presented.