Original Research Article

Adiposity, Muscle, and Physical Activity: Predictors of Perturbations in Heart Rate Variability

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Objectives: This study examines cross-sectional associations of indices of adiposity, lean body mass, and physical activity, with heart rate variability (HRV), a marker for parasympathetic cardiac vagal control.

Methods: The study population consists of 360 officers from the Buffalo New York Police Department. Indices of adiposity include body mass index, waist circumference, and a fat-mass index taken from dual-energy X-ray absorptiometry (DEXA) measurements. Lean body mass indices were derived from DEXA measurements of trunk mass and extremity lean mass. Physical activity was measured using a 7-day self-report questionnaire. HRV was obtained from 5-min electrocardiogram measurements by means of parametric spectral analysis resulting in estimates for high-frequency (HF) and low-frequency (LF) HRV.

Results: Both HF and LF HRV were significantly associated with markers for adiposity, two components of lean mass and physical activity with all associations being in the expected direction except that for trunk lean mass. This unexpected result is explained by the possibility that trunk mass is a marker for visceral adiposity rather than lean mass. Body mass index did not explain any additional variance in HRV above and beyond waist circumference and the DEXA indices.

Conclusions: Higher levels of physical activity, lower levels of markers for central adiposity and higher lean mass in the extremities predict higher levels of HRV in this population of police officers. This association between modifiable risk factors and markers for autonomic function suggest possible interventions that may improve health and performance. Am. J. Hum. Biol. 00:000–000, 2013. © 2013 Wiley Periodicals, Inc.

Resting heart rate (HR) variability (HRV) is a marker of vagal parasympathetic cardiac control (Camm et al., 1996; Denver et al., 2007; Sandercock et al., 2008). This control system slows HR, moving the heart toward a resting state, and thereby facilitating energy restoration (Thayer et al., 2010). Normally, it is in dynamic balance with the sympathetic nervous system, which mobilizes the heart to expend energy in response to challenges. Together, these two systems form the two branches of the autonomic nervous system (ANS).

The ANS, in concert with the hypothalamic–pituitary–adrenal (HPA) axis, plays a key role in physiological responses to stressors (McEwen, 1998; McEwen and Lasley, 2002; McEwen and Wingfield, 2003). The ANS is a system that "errs on the side of caution—when in doubt prepare for the worst—thus maximizing survival and adaptive responses" (Thayer and Lane, 2007; Thayer and Sternberg, 2006). This tendency, coupled with prolonged and repetitive exposure to stressors, leads to chronic "dampening" of the inhibitory branch of this system, thereby allowing the excitatory sympathetic branch to dominate. This phenomenon, called vagal withdrawal, is characterized by reduction in HRV—particularly high-frequency (HF) components—and represents an inability of cardiac brake control to return the system to a resting state after sympathetic arousal (McEwen and Lasley, 2002; Porges, 1995, 2007).

The effects of vagal withdrawal go beyond regulation of cardiac control, implicating an array of connections with stress exposure, anxiety disorders, disorders of attention, and social engagement as well as cardiovascular risk and cardiovascular disease (CVD) (Beauchaine et al., 2007; Porges, 2007; Schroeder et al., 2003, 2005; Thayer and Brosschot, 2005; Thayer and Lane, 2007; Thayer and Sternberg, 2006; Thayer et al., 2010). Lower levels of vagal control, measured by decreased HF HRV, is associated with risk factors for CVD, including the modifiable factors of poor physical fitness and obesity (Thayer et al., 2010).

Measuring obesity is problematic. Differences among people in body habitus reflect differences in proportions of adiposity, muscle mass, and bone mass. The body mass index (BMI, weight/height^2 [kg/m^2]) has a long history as a surrogate measure of adiposity, but is unable to distinguish among constituent partitions of fat, lean, and bone mass. Within some population studies, including the Buffalo Cardio-Metabolic Occupational Police Stress (BCOPS) cohort, morphological partitions are better predictors than BMI of CVD and diabetes risk (Kelly et al., 2009; Sharp et al., 2012).

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This study examines how well (1) BMI, (2) measures of adiposity and lean mass derived from dual-energy X-ray absorptiometry (DEXA) (Haarbo et al., 1991), and (3) physical activity correlate with HRV.

METHODS

The BCOPS study is a collaboration between the National Institute for Occupational Safety and Health and the University at Buffalo, The State University of New York, established in 2001 with a limited pilot study (Violanti et al., 2006). The target population is the Buffalo Police Department. Recruitment for the full baseline examination of 464 officers commenced May 21, 2004, the first participant was examined on June 4, and the last in October 2009. During recruitment the eligible target population decreased from 710 in 2004 to 635 in 2007. The BCOPS study is now a longitudinal study; the focus of this article is on cross-sectional data from the baseline study.

Of the 464 officers examined at baseline, 360 had adequate data to assess HRV as well as complete data on all other covariates. Race strata were limited to Blacks and Whites, with Hispanics ($n = 7$) included with Whites. The cohort includes men and women. All participants provided signed written consent. Human subjects review board oversight is described in a previous paper (Violanti et al., 2006).

Study design

Analyses reported in this article reflect a cross-sectional design. Irrespective of design, the associations being assessed reflect well-described hypothesized causal associations reported in the peer reviewed literature. Similarly, scientific evidence suggests that population changes in obesity, muscle mass, and physical activity coevolve with changes in CVD and diabetes risk, including HRV; thus, any "snapshot in time"—i.e., cross section—will reflect this coevolution and potentially associations with underlying indicators of HRV function. This logic is sufficient to assess the fundamental question, "How do variations in physical activity as well as fat and lean mass correlate with variation in heart rate variability?": with the caveat that results of cross-sectional studies cannot imply causal association, but may be consistent with such.

Clinic examination

All measurements for the BCOPS clinic examination reported here were obtained on the same day for each participant. Participants were instructed to avoid the following after 10 pm on the night before the day of examination: eating or drinking anything but water, strenuous physical exercise, caffeinated beverages, alcoholic beverages, and use of tobacco. All officers were given a standardized breakfast around 8:30 am after the fasting blood draw and before other study components.

Heart rate variability measurements

Electrocardiograms (ECG) were used to derive HRV, and were obtained and processed according to standard methods published by the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology (Camm et al., 1996). ECG measurements derived from a three electrode lead setup, and data were abstracted from a voltage time series of lead II during the carotid ultrasound examination. ECG voltages were sampled at 2000 Hz and digitally captured using the Biopac Systems, MP100 system/software with accompanying ECG Amplifier (C series), appropriate ECG leads, cables, electrodes, and computer for recording and data processing.

Officers were supine and resting for 5 min before ECG data for HRV analyses were recorded. The time of day for the ECG examination varies from morning at 9:15 am to around 12:00 pm depending on officer placement in the clinic schedule.

Sequence time markers were placed to indicate beginning and ending of the examination. Resting ECG time series were extracted from the first 5 min of examination, and processed using an automated data adaptive QRS detection package that inserts a marker at each proposed R wave (gBS analyze advanced biosignal processing system with ECG toolbox, Guger Technologies, Graz, Austria, www.gtec.at).

A QRS interval-clustering step created clusters of QRS intervals within a participant's ECG record based on how well the QRS intervals correlated with each other. Atypical QRS intervals as well as noise or movement artifact are thus identified, allowing special handling during data editing. The last step includes visual inspection of the ECG overlaid with QRS markers and hand editing of R wave markers: e.g., removal of markers not located on R waves, addition of markers that were not detected by software, and identification of markers for deletion of isolated ectopic beats (Lippman et al., 1994). Visual identification of ectopic beats was validated by using several versions of an impulse rejection filter (McNames et al., 2004). Generally, data from participants had no or very few isolated ectopic beats, and were easily identified. ECGs having a large number of ectopic beats or irregular QRS intervals led to exclusion of the participant from data analyses.

Of 447 officers with resting ECGs, 25 reported a history of irregular heartbeats and were excluded. Thirty-two additional officers had significant evidence of irregular beats or abnormal QRS intervals making consistent marking of R waves impossible, and were excluded. Three hundred ninety (390) participants had high quality ECG data sufficient for analysis.

Compared to time domain statistics, frequency domain methods are recommended for short-term stationary measurements of HRV. This is because theoretical and physiological interpretations of the HF component are conceptually well grounded (Camm et al., 1996). Accordingly, for each officer R-to-R interval time series were processed using the R statistical computer programming language by cubic spline interpolation to provide a series with equal sample increments at two samples per second. The interpolated time series was detrended using a smoothness priors method (Tarvainen et al., 2002). This produces equally spaced mean-zero time series data with no long-term trends, thus meeting assumptions of spectral analysis models. Next, data were processed using a parametric autoregressive spectral analysis of order 16 (Boardman et al., 2002). The HF component of HRV is defined as the area under the power spectral density from 0.15 to 0.4 Hz; the low-frequency (LF) component is defined between frequencies 0.04 to 0.15 Hz; and two HRV variables were generated for each participant.

DEXA, anthropometry, and physical activity measurements

DEXA (Hologic QDR-4500A; Hologic, Waltham, MA) measured whole body and segmental fat-mass, bone-

mass, and lean-mass (Tothill and Hannan, 2000). The same machine performed all scans on all participants. Duplicate measurements on 40 officers allowed calculation of coefficients of variation (CV): respectively, 1.4, 0.9, and 0.5% for total fat-mass, bone-mass, and bone density. Daily manufacturer quality control phantom measurements ensured no drift. During recruitment no software upgrades occurred.

Certified study staff performed anthropometric measurements according to standard protocols, including height and weight; respectively, measured with shoes removed and recorded to the nearest 1/2 cm, and rounding up to the nearest 1/4 lb then converted to kg. Waist circumference was measured twice to the nearest 0.5 cm (thrice if twice differed > 0.5 cm): standing after exhalation, arms at side, at the midpoint between the highest point of the iliac crest and lowest part of the costal margin in the midaxillary line.

Hours of moderate, hard, and very hard physical activity during the previous weekdays and weekend were estimated from the 7-day Physical Activity Recall questionnaire (Ma et al., 2011; Sallis et al., 1985). This "index" represents a weighted sum score of hours spent in various types of activities; weights of "1," "2," or "3," respectively, associated with "moderate," "hard," and "very hard" activities.

Statistical methods

All analyses used SAS software, version 9.2 (Bailer et al., 2010). The BMI was calculated as weight/height^2 (kg/m^2). Fat-mass and lean-mass indices were derived from DEXA measurements. The indices, based on powers of height and bone-mass, were developed to standardize for height, plus bone-mass in the case of the lean-mass index [fat-mass index (FMI) = fat-mass/height$^{1.4}$ (kg/m$^{1.4}$); lean-mass index (LMI) = lean-mass/height$^{1.2}$/bone-mass$^{0.3}$ (kg/m$^{1.2}$/kg$^{0.3}$)]. The power coefficients in these indices were calculated under the constraint that the resulting indices have zero correlation with height or bone-mass. Details of this analysis are described elsewhere (Sharp et al., 2012). Indices for two partitions of lean-mass—trunk (LMI_t) and collective extremities (LMI_e)—were created using the same power coefficients for height and bone-mass (Sharp et al., 2012). Using these indices in populations other than BCOPS remains to be validated (Sharp et al., 2012).

Natural logarithm transforms of the HF (LnHF) and LF (LnLF) HRV variables and the physical activity (LnPA) variable were done to normalize skewed distributions.

Univariate means, standard deviations, and bivariate correlations were calculated for variables of interest. For each of the two HRV variables—LnHF and LnLF—a series of multiple regression models were constructed with each as dependent variable. All models controlled for sex, but not race for reasons presented in results.

A series of models are presented to examine the relative contribution of each variable of interest in explaining variation in HRV along with the joint effects of meaningful combinations of variables. Three distinct models form a series set (see Table 2 as an illustration); two of these models only include a single class of variable(s)—a class may include more than one variable; the third model includes both classes of variable(s). All models reflect a strategy of partial F-tests of nested multivariable regression models (Neter et al., 1985). The multiple R^2, a measure of explained variance, is the focus of these analyses. The partial F-test assesses the statistical significance of adding groups of variables to a more parsimonious model; differences in R^2 magnitudes are related to this test. The order in which a class of variable is introduced is a key aspect of this form of analysis.

The individual regression models included in this analysis are summarized in the bulleted list below, various combinations of which are presented in Tables 2 and 3. All models are adjusted for sex. For models with the dependent variable LnHF, the anthropometric variables (Anthros) include Waist circumference, LMI_t, and LMI_e; and for the dependent variable LnLF, the Anthros variables are Waist and LMI_e; these choices reflect preliminary analyses identifying consistently statistically significant individual variables among all models. In the case of LnLF, any unique model that included LMI_t within Anthros (Models 1, 3, 6, 7 below) produced statistically insignificant coefficients (results not shown), varying from $0.46 \leq P \leq 0.72$. Waist tended to perform more consistently than fat-mass indices, and their high correlation ($r = 0.87$–0.89) suggest they measure the same construct—adiposity.

Models 1 and 2 below focus on the relative variance explained by (a) the Anthros variables as a group and (b) age. Model 3 represents the combined effects of the Anthros variables and age. Model 4 represents the age and sex adjusted HRV variance explained by BMI before the Anthros variables have been accounted for and Model 6 the variance explained by BMI after the Anthros variables have been added. Model 5 represents the variance explained by physical activity (LnPA) after adjustment for sex and age, and Model 7 the addition of the Anthros variables.

- Model 1 includes sex and joint Anthros variables.
- Model 2 includes sex and age.
- Model 3 combines models 1 and 2 and includes sex, age, and Anthros.
- Model 4 adds BMI to Model 2.
- Model 5 adds LnPA to Model 2.
- Model 6 adds Anthros to Model 4.
- Model 7 adds Anthros to Model 5.

In addition, regression coefficients and standard errors are reported for selected models.

To examine the multivariate structure of the associations between the dependent variables HR and HRV (i.e., HR and HR control) and the anthropometric and physical activity measures, a canonical correlation analysis was conducted in which sex and age were included as covariates. Canonical correlation is a multivariate method that estimates the correlation between linear combinations of two sets of variables. Canonical correlation analysis results in new variables, known as canonical variables, which represent linear combinations of the two sets of variables of interest. These newly created variables are referred to as the first, second, and possibly higher order canonical variables. The first canonical correlation, the correlation between the first two canonical variables, explains the maximum amount of correlation that can be explained by two linear combinations of the two sets of measured variables. The second canonical correlation explains the remaining correlation that can be explained

TABLE 1. Simple statistics and correlations[a] of selected heart rate variability, demographic, anthropometric, and physical activity variables in 360 police officers.

Variables	*Mean* ± *SD*[b]	Sex	Age	BMI	Waist	LMI_t	LMI_e	LnPA	LnHF	LnLF
Sex: ♂=0,♀=1	0.256	1.0								
Age, yrs	42.1 ± 7.66	−0.864	1.0							
BMI [b], kg/m^2	29.0 ± 4.40	−0.394	0.081	1.0						
Waist [b], cm	94.2 ± 13.6	−0.587	0.168	0.857	1.0					
LMI_t [b], $kg/m^{1.2}/kg^{0.3}$	11.7 ± 1.87	−0.669	0.088	0.807	0.808	1.0				
LMI_e [b], $kg/m^{1.2}/kg^{0.3}$	11.4 ± 1.87	−0.760	0.006	0.747	0.722	0.847	1.0			
LnPA [b], see text	2.66 ± 1.04	0.016	0.030	−0.093	−0.072	−0.037	−0.067	1.0		
LnHF [b], *ln*[$msec^2$]	4.96 ± 1.13	0.147	−0.292	−0.098	−0.194	−0.148	−0.035	0.149	1.0	
LnLF [b], *ln*[$msec^2$]	5.31 ± 0.91	−0.078	−0.247	−0.096	−0.125	−0.027	0.071	0.134	0.699	1.0
HR [b], beats/min	64.0 ± 8.82	0.058	−0.007	0.120	0.115	0.059	−0.042	−0.175	−0.482	−0.329

[a]Two-tail critical values of **correlation coefficient** for H_o:ρ=0: P=0.05, **0.103**; P=0.01, **0.136**; P=0.001, **0.173**; P=0.0001, **0.204**
[b]SD: standard deviation; Sex: "*Mean*" is proportion of females, correlations are point-biserial; BMI: Body Mass Index; Waist: waist circumference; LMI: Lean Mass Index - t ≡ trunk, e ≡ extremities; LnPA: natural logarithm (*ln*) of Physical Activity Index; LnHF: *ln* of high frequency heart rate variability; LnLF: *ln* of low frequency heart rate variability; HR: heart rate. See text for definitions.

by an orthogonal set of linear combinations of the two sets of measured variables and so on for higher order canonical correlations until there are no more degrees of freedom or all information in the two sets of variables is explained. In this analysis, one set of variables included HRV variables and HR, and the other, anthropometric variables and physical activity. Specifically, the first "Y" canonical variable, labeled HRV1, included LnHF, LnLF, and HR; the first "X" canonical variable, labeled *Anthro1*, included Waist, LMI_t, LMI_e, and LnPA. The second canonical variables, which include the same variables as HRV1 and *Anthro1* are labeled HRV2 and *Anthro2*. By definition HRV2 and *Anthro2* are linearly independent of HRV1 and *Anthro1*.

RESULTS

Even at a Type I error rate of 0.1, race was not associated with LnHF or LnLF, nor did race alter by more than 10% associations of other covariates with these two dependent variables in any regression model (results not shown). In keeping with parsimony, race was not included as a covariate in regression models.

Means, standard deviations, and bivariate correlations of the variables used in analyses of this article among the 360 police officers are presented in Table 1. Notable correlations are (1) sex and age, reflecting the more recent recruitment of women into the Buffalo Police Department, and sex with BMI (r = -0.394) as well sex with waist, LMI_t, and LMI_e (r = -0.587 to −0.760); (2) BMI with waist, LMI_t, and LMI_e (r = 0.747–0.857); and (3) LnHF and LnLF (r = 0.699). Correlations involving LnPA are notably small—all >-0.2 or <0.2, and statistically significant at $P \leq 0.05$ for only the three HR variables.

In models that already include sex as a covariate, the proportion of variance of LnHF explained by three classes of variables—Anthros, LnPA, or Age—is significant for each individual class (Fig. 1: Anthros 0.077 or 7.7%, LnPA 2.1%, age 7.9%). In a "grand" model including all three classes, when each class is introduced last the proportion of explained variance for Anthros and age decreases, 5 and 5.1%, respectively, but increases to 2.6% for LnPA. This joint model explains 2.5% of variance by the *joint* associations among these three classes of variables, and cannot be attributed to any class—a reflection of the vagaries of multicollinearity. The patterns reflected in Figure 1 are reproduced in the tables to follow, which detail

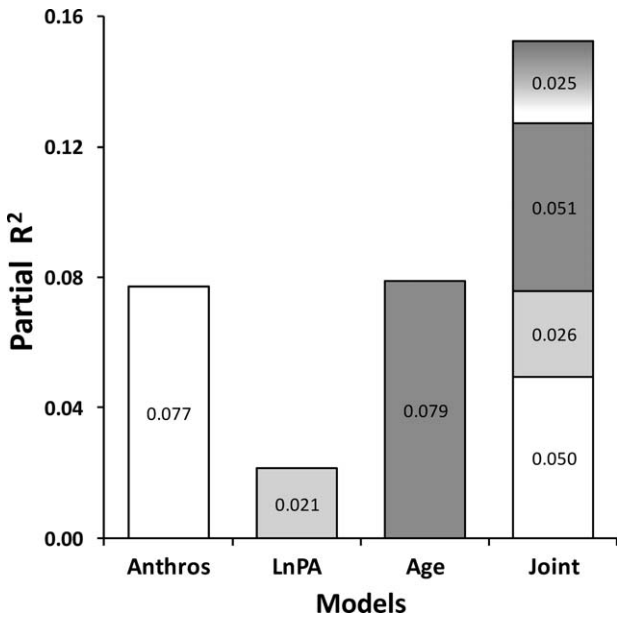

Fig. 1. Explained variance (partial R^2) of the natural logarithm of high-frequency heart rate variability power spectral density (LnHF) for individual models of DEXA/anthropometric variables (Anthros), the logarithm of physical activity (LnPA), and age as well as a joint model containing all variables. Gradient segment (labeled 0.025) in "Joint" bar represents explained variance which cannot be attributed to one of the individual classes of variables.

results of the three sets of models described previously in the Methods section.

The Anthros variables alone explain between 6 and 8% (0.06–0.08 as a proportion) of variance in LnHF and LnLF, as does age (Table 2). A joint model including both classes of independent variable reduces the independent proportion for each class to 4–5% with 2–3% being explained by joint associations and not attributable to any given class. All of these proportions are highly statistically significant, and validate an inference that age is a covariate to be included in any model of LnHF or LnLF.

The role of BMI as a covariate in models of explained variance for LnHF and LnLF is either nonexistent for LnHF or attenuated to nonexistent for LnLF by joint inclusion of Anthros variables (Table 3: Models 4 and 6). The role of LnPA, however, is notably significant for both

TABLE 2. Explained variance[a] in distribution of two heart rate variability[b] variables by 1) anthropometric measures,[c] 2) age, and 3) their joint effects in 360 police officers.

		Variance Explained by Variable Class as Partial R^2					
Variable	Model[a]	Mult R^2	1) Anthros[c]	2) Age	3) Joint[d]	*F*-value[e]	*P*-value
LnHF[b]	1	0.0986	0.0771	—	—	10.12	<0.0001
	2	0.1003	—	0.0788	—	31.3	<0.0001
	3	0.1476	0.0473	0.0490	0.0298	12.9	<0.0001
		F-, *P*-value[f]	6.55, 0.0003	20.3, <0.0001	—	—	—
LnLF[b]	1	0.0737	0.0675	—	—	12.98	<0.0001
	2	0.0708	—	0.0646	—	24.8	<0.0001
	3	0.1135	0.0428	0.0399	0.0247	14.34	<0.0001
		F-, *P*-value[f]	8.55, 0.0002	15.9, <0.0001	—	—	—

[a]Explained variance after control for sex in all models. Model 1 adds anthropometric variables only; Model 2 adds age only; and Model 3 adds both.
[b]Natural logarithm of high frequency (LnHF) or low frequency (LnLF) components of heart rate variability. See text.
[c]Anthropomentric variables (Anthros) include waist circumference, trunk lean mass index (LMI_t), and extremities lean mass index (LMI_e) for LnHF; for LnLF, waist circumference and LMI_e.
[d]Partial R^2 of *Joint* association is partial R^2 for addition of anthropometric variables *and* age, minus partial R^2 when anthropometric variables are added after age, minus partial R^2 when age is added after anthropometric variables. All paths lead to Model 3.
[e]F-test for addition of *all* variables identified in columns 1) and 2) to a model containing sex.
[f]Pertains to Model 3 only; F-tests, P-values for addition of variable class last in Model 3.

TABLE 3. Explained variance[a] in distribution of two heart rate variability[b] variables by 1) anthropometric measures[c], 2) BMI, 3) LnPA, and 4) joint effects in 360 police officers.

		Variance Explained by Variable Class as Partial R^2						
Variable	Model[a]	Mult R^2	1) Anthros[c]	2) BMI	3) LnPA	4) Joint[d]	*F*-value[e]	*P*-value
LnHF[b]	3	0.1476	0.0473	—	—	—	6.55	0.0003
	4	0.1012	—	0.0009	—	—	0.34	0.56
	5	0.1244	—	—	0.0241	—	9.79	0.0019
	6	0.1476	0.0465	0.0000	—	0.0008	4.90	0.0007
		F-, P-value[f]	6.41, 0.0003	<0.01, 0.996	—	—	—	—
	7	0.1740	0.0496	—	0.0263	−0.0022	7.87	<0.0001
		F-, P-value[f]	7.06, 0.0001	—	11.26,0.0009	—	—	—
LnLF[b]	3	0.1135	0.0428	—	—	—	8.55	0.0002
	4	0.0865	—	0.0157		—	6.14	0.0137
	5	0.0914	—	—	0.0206	—	8.07	0.0048
	6	0.1149	0.0284	0.0014	—	0.0144	5.89	0.0006
		F-, *P*-value[f]	5.68, 0.0037	0.56, 0.46	—	—	—	—
	7	0.1316	0.0402	—	0.0181	0.0025	8.27	<0.0001
		F-, *P*-value[f]	8.20, 0.0003	—	7.36, 0.0070	—	—	—

[a]Explained variance after control for sex *and* age in all models. Models 3, 4, and 5 respectively add anthropometrics, BMI, or LnPA only; Model 6 adds anthropometrics *and* BMI; Model 7 adds anthropomentrics *and* LnPA.
[b]Natural logarithm of high frequency (LnHF) or low frequency (LnLF) components of heart rate variability. See text.
[c]Anthropomentric variables (Anthros) include waist circumference, trunk lean mass index (LMI_t), and extremities lean mass index (LMI_e) for LnHF; for LnLF, waist circumference and LMI_e. BMI: body mass index (kg/m^2). LnPA: natural logarithm of physical activity (see text).
[d]Partial R^2 of *Joint* association is partial R^2 for addition of anthropometric variables *and* BMI or LnPA, minus partial R^2 when anthropometric variables are added *after* BMI or LnPA, minus partial R^2 when BMI or LnPA is added *after* anthropometric variables. All paths lead to Model 6 (BMI) or Model 7 (LnPA).
[e]F-test for addition of *all* variables identified in columns 1) to 3) to a model containing sex and age.
[f]Pertains to Models 6 & 7 only; *F*-test, *P*-value for addition of variable class last in respective model.

HRV variables (Table 3: Models 5 and 7). For LnHF, the proportion of variance attributable to LnPA in a joint model with Anthros is larger than a model containing only LnPA, and the *joint* explained variance is negative (−0.22%) indicating the phenomenon of negative confounding.

The magnitude of regression coefficients for either LnHF or LnLF is notably attenuated for joint Anthros variables when adjusted for sex and age, but "increases" for LnPA (Table 4). Inclusion of BMI in models of LnHF has no effect on magnitude of regression coefficients, minimally inflating standard errors for LMI_t and LMI_e only. For LnLF, however, addition of BMI decreases the waist coefficient by ∼23% but increases that of LMI_e by ∼31%; the standard errors of both coefficients, respectively, inflate by 62 and 33%. Full models of LnHF containing both classes of independent variables attenuate the waist coefficient magnitude ($T = -1.75$, $P = 0.08$); but increase magnitudes for LMI_t , LMI_e , and LnPA, and have no impact on standard errors. Full models of LnLF appear to minimally alter regression coefficients and their standard errors.

Other HRV parameters reported in the literature include the root mean square successive difference (RMSSD), a time domain marker related to HF variation and SDNN, the standard deviation of the edited RR time series. While these parameters are not the main interest of this study we include some description of results based on analyses that parallel Tables 2 and 3 for those interested in comparing these results to those of other studies using RMSSD and SDNN alone. The Ln(RMSSD) had 0.96 correlation with LnHF and analyses parallel to Tables 2 and 3 resulted in very similar estimates of significance and partial correlation (data not shown) leading to identical conclusions when compared to LnHF. Similar analyses with Ln(SDNN), using the same anthropometric variables in the Tables 2 and 3 models with LnHF, did not differ in any meaningful way from results reported for LnHF and LnLF (data not shown). Conclusions based on

TABLE 4. Impact of including various co-variates on regression coefficients[a] and standard errors for models of the heart rate variability variables LnHF and LnLF.[b]

	Co-variates[b] in Model				
Predictors[b]	None	Sex, Age	Sex, Age, BMI	Full Model[a]	
Logarithm of High Frequency Heart Rate Variability (LnHF)					
Anthros					T-/P-values
Waist	−0.0211	−0.0141	−0.0141	−0.0124	−1.75
	±0.0073	±0.0072	±0.0100	±0.0071	0.080
LMI_t	−0.179	−0.159	−0.159	−0.176	−2.22
	±0.083	±0.080	±0.084	±0.079	0.027
LMI_e	0.214	0.262	0.262	0.277	4.29
	±0.059	±0.066	±0.077	±0.065	<0.0001
LnPA	0.163	0.170	0.168	0.179	3.36
	±0.057	±0.054	±0.055	±0.053	0.0009
Logarithm of Low Frequency Heart Rate Variability (LnLF)					
Anthros					
Waist	−0.0247	−0.0206	−0.0159	−0.0200	−4.05
	±0.0049	±0.0050	±0.0081	±0.0049	<0.0001
LMI_e	0.163	0.096	0.126	0.102	2.30
	±0.036	±0.045	±0.060	±0.044	0.022
LnPA	0.118	0.126	0.116	0.118	2.71
	±0.046	±0.044	±0.044	±0.044	0.007

[a]Anthropomentric variables (Anthros) included jointly in all models. Full Model includes sex, age, and all predictors, but not BMI.
[b]Refer to Table 2 for definitions of various abbrieviations.

analyses of Ln(SDNN) are less straightforward as this parameter collapses all HRV frequency components available in the HRV time series into one parameter. This parameter can be taken as a mixture of cardiac vagal control, baroflex function, and other sources of variation.

Canonical correlation analyses produce a highly significant first canonical correlate (Table 5: $r = 0.338$, $P < 0.0001$). All three HR variables load heavily into HRV1—positive correlations noted for LnHF and LnLF, and a negative correlation for HR. All three variables are uniformly correlated with *Anthro1* in the same pattern. Waist, LMI_t, and LnPA notably load into *Anthro1*—positive correlations for the first two and negative for LnPA; but LMI_e does not load. A similar pattern of correlation is noted between these four variables and HRV1. These patterns were consistent for the first canonical correlation when combinations of other anthropometric and DEXA variables were included. The second canonical correlation (HRV2 vs *Anthro2*, $r = 0.189$) was statistically significant ($P = 0.04$) for this set of HR and anthropometric/DEXA variables; however, inclusion of other anthropometric and DEXA variables produced varying patterns and varying occasions of statistical significance. These are not reported, although there was a tendency for LMI_e to consistently load as the dominant variable into *Anthro2*.

DISCUSSION

Waist circumference and DEXA lean-mass indices explain significant proportions of variation in both HF and LF components of the power spectral densities of HRV. In addition and independently of morphological assessments of adiposity and muscle mass, an indicator of physical activity also explains significant proportions of variation in these two measures of HRV; BMI, however, does not.

Associations involving LMI_t and LMI_e

Associations of LnHF involving LMI_t appear counterintuitive; the expectation is that a high lean-mass index is associated with risk protection. The opposite is noted, even when adjusting for fat-mass via inclusion of waist circumference, or FMI (not shown), in joint models. This finding is consistent with a recent report from CARDIA (Sood et al., 2011). Women with asthma have a higher trunk lean-mass index, even after control for fat-mass, compared to women without asthma. This suggests that, "DEXA-assessed 'lean' mass is not entirely fat-free but includes the smaller and highly metabolically active ectopic fat within the skeletal muscle and viscera." (Sood et al., 2011). In BCOPS, the large positive correlation of LMI_t with waist ($r = 0.808$, Table 1; $r = 0.693$, sex and age partialled out) is consistent with this index reflecting the effect of ectopic fat, particularly within viscera (Cornier et al., 2011).

Associations of LnHF and LnLF with LMI_e appear to reflect an expected relationship that this index represents muscle mass. High variability, an indicator of "healthy" response of HR to perturbation, is associated with higher values of LMI_e.

TABLE 5. Canonical correlates[a] of heart rate variables with anthropometric and physical activity variables.

Variables[b]	HRV1[a]	*Anthro1*[a]
HRV1	1.0	0.338
Anthro1	0.338	1.0
LnHF	0.794	0.268
LnLF	0.756	0.255
HR	−0.863	−0.291
Waist	−0.212	−0.628
LMI_t	−0.136	−0.403
LMI_e	0.012	0.035
LnPA	0.202	0.599

[a]First canonical correlate: Wilks' $\lambda = 0.853$, $F = 4.79$, $P < 0.0001$
[b]See Table 1, footnote b for definitions of variables.

Heart rate variability

The HF component of HRV as a marker for cardiac vagal control is the main parameter of interest in this study. It has clear physiological interpretation as a marker of parasympathetic function and its capacity to provide tonic inhibition of sympathetic arousal during normal everyday adaptation. We have reported the LF component of HRV for completeness, yet its interpretation as a marker for cardiac sympathetic tone remains controversial. Recent experimental results suggest that the LF component is likely a mixture of parasympathetic vagal activity and baroflex function (Moak et al., 2007; Rahman et al., 2011). The correlation between HF and LF found in the present study ($r = 0.699$) is consistent with that reported in other studies that report this statistic (Moak et al., 2007). This means that about 50% of the between-person variation in either of these two parameters can be explained by variation in the other parameter. While it is tempting to point to the magnitude of this correlation as meaning that the HF and LF component of HRV share—in part—the same physiological origin (e.g., baroflex function), a more plausible interpretation in cross-sectional data is that this correlation is partially driven by varying levels of ANS function related to aging, cardiovascular risk factors, stress and other chronic exposures, along with underlying shared physiological origin related to inhibitory control of HR by the parasympathetic nervous system.

The associations between physical activity, markers of adiposity and HRV reported in this study are consistent with previous findings. In a recent review of the literature on autonomic function as measured by HRV, Thayer and others (2010) propose an autonomic imbalance model as a "common pathway" explaining associations between workplace stress exposure and CVD. He also points out that modification of risk factors like adiposity and lack of physical activity may improve autonomic function and help prevent subsequent disease. In adult police officers, the associations of physical activity, markers for lean muscle mass, and central adiposity with HRV reported in this study are consistent with this common pathway model. These associations are present in children and adolescents as well as adults, with the parasympathetic or cardiac vagal control component of HRV (HF) being consistently lower for obese individuals (Gutin et al., 2000, 2005; Rabbia et al., 2003; Windham et al., 2012). The presence of these associations from childhood through adulthood is consistent with the coevolution of changes in obesity, muscle mass, and loss of physical activity with changes in cardiac vagal control.

One possible mechanism that may explain associations between central adiposity and HRV is insulin resistance (Lindmark et al., 2003, 2005). Lindmark et al. (2003) reported results supporting the hypothesis that altered ANS function as measured by HRV may lead to insulin resistance, which can then lead to central adiposity (Girod and Brotman, 2003). Another study by the same group provides evidence that the association between visceral adiposity and insulin resistance may be partially mediated by alterations in ANS reactivity (Lindmark et al., 2005). The relationships between central adiposity, physical activity and insulin resistance have been described as bidirectional, with insulin resistance and decreased physical activity being potential causes of central adiposity, while decreased physical activity and central adiposity are also thought to cause insulin resistance (Girod and Brotman, 2003), therefore, causal direction is less important than the observation that ANS activity may play a role in these relationships. The authors of these studies also note that "it is not clear at present what the mechanisms are that explain these associations." Research examining the relationship between adipose tissue and the ANS in animal studies is ongoing, and suggestive of interactions between insulin resistance, adipose tissue and ANS function, but how these results apply to humans is not entirely clear at this time (Fliers et al., 2003; Romijn and Fliers, 2005).

Canonical correlation provides a multivariate way of describing the linear correlation between two sets of variables (Table 5). This method demonstrates the presence of a linear combination of HR and HR control variables, HRV1, where HRV loads positively and HR negatively, in significant correlation with a linear combination of anthropometric variables, *Anthro1* where indices of central adiposity (waist and LMI_t) load negatively and physical activity loads positive. Liberal interpretation allows us to think of the canonical variable HRV1 as an autonomic "fitness" component and the canonical variable *Anthro1* as an anthropometric and activity "fitness" component. The correlation between these is statistically significant ($r = 0.338$; $r^2 = 0.114$) inferring that over 10% of the cross-sectional variance in autonomic fitness is explained by anthropometric and activity fitness.

Increased aerobic physical activity and weight loss have been shown to lead to improvements in HRV (Karason et al., 1999; Sloan et al., 2009). From the point of view of occupational health, these results point to the value of organizational changes to develop environmental contexts which support and reinforce improved physical activity and weight management. Potential impact for prevention of CVD and associated diabetic conditions are suggested by such changes.

Besides association with disease, HRV has been related to performance. There is evidence of a positive association between resting HF HRV and situational awareness measured during police shooting simulator training—a vital aspect of cognitive performance during critical incidents (Thayer et al., 2009). It remains to be seen if interventions improving HF HRV, as a marker for vagal control, will yield meaningful effects on performance as well as cardiovascular and metabolic heath. As HF HRV is a marker for system-level functioning of the cardiac, attention, and social engagement systems (Porges, 2011), there is empirical and theoretical support for conducting such investigations.

CONCLUSIONS

HF HRV, an important marker for parasympathetic inhibition of sympathetic arousal, is also related to markers for central adiposity, muscle mass, and physical activity levels. These results underscore the importance of creating environmental contexts that can reinforce increased healthy lifestyle practices both in the workplace and at home.

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