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The multidimensionality of health: associations between allostatic load and self-report health measures in a community epidemiologic study

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ABSTRACT

With social survey data from a random sample of 1252 black and white adults who participated in the Nashville Stress and Health Study, we cross-classified *biological markers of dysregulation* with *self-report health measures*. Our aim was to quantify the degree of *concordance* between them. The study collected blood and urine samples to derive a 10 component estimate of allostatic load. In addition, the computer-assisted interview included an array of self-report measures such as self-perceived health, doctor-diagnosed diseases, bed days, and activity limitations. Allostatic load and the self-report measures were dichotomised. Modest concordance was observed between allostatic load and self-perceived health (OR = 1.742), doctor-diagnosed diseases (OR = 2.309), bed days (OR = 1.103), activity limitations (OR = 1.778), and ill on any self-report health measure (OR = 1.700). The self-report measures were significantly predictive of allostatic load, with the exception of bed days. Further, there was little evidence to suggest that race, sex, education, or past year depression moderated the level of concordance. Our findings support the hypothesis that biological markers and self-report measures could be used in tandem when specifying an individual's health status, and the distribution of population health.

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Allostatic load; biomarkers; concordance; dysregulation; illness; self-perceived health

Background

Rather than collaborating to address issues of health equity, researchers often allow disciplinary boundaries to hinder progress toward explaining what being healthy means, why health is socially distributed, and how population health can be improved. Use of biomarkers in basic research (see Chae et al., 2014; Geronimus, Hicken, Keene, & Bound, 2006; Needham et al., 2013; Needham, Fernandez, Lin, Epel, & Blackburn, 2012; Seeman, Singer, Rowe, Horwitz, & McEwen, 1997; Seeman, Singer, Ryff, Love, & Levy-Storms, 2002), a critical advance necessary for demonstrating how social inequality 'gets under the skin' and 'how our bodies tell stories' (Epel et al., 2004; Green & Darity,

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2010; Krieger, 2005; Miller, Chen, & Parker, 2011; Taylor, Repetti, & Seeman, 1997), stimulated further debate about disciplinary distinctions inherent to the measurement of health status. One aspect of the debate regards the distinction between *objective* and *subjective* health indicators, and implicitly, the value of self-report health measures commonly used in community epidemiologic studies. Specifically, some public health researchers, epidemiologists, and physicians criticise health-related research that relies on respondents' self-reports and perceptions.

When estimating health status, biological markers such as leukocyte telomere length, body mass index (BMI), cortisol, C-reactive protein (CRP), and so on, appear to offer advantages over popular self-report measures (Karlamangla, Gruenewald, & Seeman, 2012). First, biological markers minimise present state bias. When respondents are feeling particularly healthy *or* unhealthy, asking them to assess their status induces bias. In contrast, assessing assays in blood or urine or saliva does not depend upon a respondent's present state. Second, biological markers eliminate bias related to health-care access. If researchers ask people to report on serious health problems diagnosed by a health-care provider, then those reports depend upon routine access to (and probably, high quality) health care. Third, biological markers often capture reactivity and nascent disease states rather than experienced symptomatology and/or decreased function (Karlamangla et al., 2012). Consequently, scholars may predict when a person is at risk for developing a disease before the person becomes conscious of their deteriorating health status. Fourth, biological markers capture health at the very moment in time they are measured, which facilitates the time ordering of self-reported and retrospective variables in cross-sectional data. Finally, biological markers often index the function of multiple, interdependent biochemical systems inside the body. For example, *allostatic load* (Dowd, Simanek, & Aiello, 2009; McEwen, 1998, 2002; McEwen & Gianaros, 2010, 2011; McEwen & Seeman, 1999; McEwen & Stellar, 1993; McEwen & Wingfield, 2003) a summary of biochemical dysregulation according to concatenation of deleterious scores across several biomarkers, is configured typically to capture cardiovascular, metabolic, hypothalamic-pituitary-adrenal (HPA) axis, autonomic nervous system and sympathetic nervous system, and inflammatory system dysregulation. (For more information on allostasis and allostatic load, see Allostatic load and allostasis (2009).) Moreover, using a summary statistic such as allostatic load avoids the problem of strong correlations among certain biomarkers (see Coffman & Richmond-Bryant, 2015).

Biomarkers are not without limitations but most of those limitations are controllable including such issues as standardised procedures for specimen collection, methodological precision during estimation, and capturing subjects' prescription medication use. Therefore, given the benefits and limitations just outlined, one might argue that health status is estimated best by biological markers. However, we suggest and will argue that health-related perceptions and experiences are meaningful for contextualising health status, and that measures of *illness* (i.e. subjective health) add vital information beyond that provided by biological markers. What social scientists know and have demonstrated is that: (1) health is more than biology (rather, belief can become biology) (Cousins, 1989; Ray, 2004); (2) the absence of disease (or dysregulation) is not the presence of health (Jahoda, 1958; Keyes, 1998, 2002); and (3) perceptions and social relations are real in terms of their consequences for health behaviour specifically, and social behaviour generally (Ferraro & Farmer, 1999; Merton, 1968; Thomas & Thomas, 1928).

We theorise therefore that an individual's true health status may exist at the convergence of dysregulation and illness. Exploring that convergence allows scholars to explain in detail how the measurement of health status depends simultaneously on biology, psychology, sociology, and culture (see Fadiman, 1997; Kleinman, 1988; Meador, 2005). Disease generally follows dysregulation of a bodily system or abnormal functioning therein, and hence a person may experience a decline in their health status. However, a person can also have biochemical dysregulation but be completely oblivious to it in terms of how they perceive their health status. This is so because most individuals perceive themselves as healthy until symptoms interfere with activities of daily living or cause pain and discomfort. In contrast to dysregulation, illness is a subjective state – such that one perceives a decline in their physiological functioning. For example, the *sick role* is a concept capturing the idea that there are expectations and negotiations that accompany *feeling ill* and those expectations and negotiations are guided by social norms and constraints (Parsons, 1951). In sum, we argue that the parallel absence of biological dysregulation and perceived illness may best capture healthiness.

The present study

Whereas some studies link specific biomarkers with specific diseases (see Coffman & Richmond-Bryant, 2015), to our knowledge, this is the first study to assess concordance between allostatic load and popular self-report health measures. Granting potential reciprocity between the body, mind, and social environment in producing health status, we expect modest concordance between allostatic load and the self-report health measures, revealing four latent population groups: (1) *healthy individuals*, (2) *unhealthy individuals*, (3) *ill individuals*, and (4) *dysregulated individuals* (see Figure 1). Healthy individuals do not show signs of biochemical dysregulation and report that they feel well and capable. Unhealthy individuals show signs of biochemical imbalance and report feeling ill and incapacitated. Ill individuals report poor health, but their bodies do not indicate biological

		Biological Dysregulation	
		No	Yes
Poor Self-Reported Health	No	Healthy Individuals	Dysregulated Individuals
	Yes	Ill Individuals	Unhealthy Individuals

Figure 1. Conceptual representation of concordance between objective and subjective measures of health.

dysregulation. Lastly, dysregulated individuals have biomarkers that suggest high risk of disease, but they feel fine and report no health limitations.

As noted in the previous section, some studies have advanced concepts like flourishing, illness, well-being, sickness, and so on, that are more complex than the four-part scheme we introduce here, but those studies are mainly theoretical and have neglected the empirical utility of biomarkers. In this study, we address the multidimensionality of health with the intent of speaking to medical sociologists, public health researchers, and epidemiologists, and consequently hope that these groups of scholars will recognise that objective and subjective measures of health are simultaneously valid.

We address our expectations using survey data from the Nashville Stress and Health Study (NSAHS). As hypothesised, we find that allostatic load and the self-report measures correlate significantly yet modestly. Accordingly, we suggest that healthiness is probably best estimated by combining biochemical regulation *and* sanguine perceptions. Neither race, sex, education, nor past year depression shifts associations between biological markers and self-report measures. As such, our findings support the *bio-psycho-social model* and we conclude that those concerned with health equity must embrace multiple truths about valid measurement of an individual's health status, and the distribution of population health.

Methods

Data and sample

The NSAHS is a random sample of 1252 black men and women (unweighted $n = 627$) and white men and women (unweighted $n = 625$) living within Davidson County, Tennessee (Vanderbilt University IRB # 100165). Davidson County (approximately 630,000 residents) includes and extends beyond the city of Nashville, Tennessee.

To obtain the sample, we randomly selected 199 block groups within Davidson County. Survey Sampling International Corporation then provided us with 7000 randomly selected addresses sampled from these block groups in proportion to population size. During the screening phase, screeners obtained the names, sex, age, race, and educational attainment of adults between 25 and 65 years old who were resident in 6490 of the 7000 households. We stopped short of screening the full 7000 due to budget and time constraints. We stratified a portion of the block groups and oversampled black households as black men and women represent approximately 28% of Davidson County residents (according to 2010 Census data) and we desired a final sample that included enough respondents who self-identified as black to permit within-group analyses by race. Of the 6490 household screens, 1411 households were ineligible due to age or race restrictions of the study design, 1375 households refused to complete the screening, and 676 households were vacant or non-residential addresses. Therefore, the number of household screens that included eligible (and potential) respondents was 3028. The screening phase lasted from July 2010 to March 2011.

We randomly sampled 2400 potential respondents from the 3028 successful and eligible household screens with equal numbers in the following categories: white women (600), black women (600), white men (600), and black men (600). Only one potential respondent was selected per household. We successfully interviewed 1252 respondents from the

randomly sampled 2400 potential respondents. Dispositions of the remaining 1148 potential respondents are as follows: (a) unable to be located/contacted (406), (b) discovered to be ineligible (96), (c) refusals (388), (d) moved from Davidson County, Tennessee since screening (162), (e) died since screening (19), (f) mentally incapable of participating in interview (23), (g) duplicate interview (1), (h) imprisoned since screening (6), or (i) never approached for interview due to budget and time constraints (47). The interviewing phase lasted from April 2011 to January 2014.

During the interviewing phase, computer-assisted personal interviews were conducted with respondents by race-matched interviewers trained by the study investigators. Interviews, which averaged more than two hours and 45 minutes in length, took place in respondents' homes or on Vanderbilt University's campus when preferred by the respondent. Within the interview, instructions were provided regarding a 12-hour urine sample and follow-up visit by a clinician. Clinicians arrived before breakfast the day after the survey was completed, retrieved the urine receptacle, drew blood samples, measured blood pressure three times spaced two minutes apart, and took measures of waist and hip, and height and weight. Clinicians also collected information on prescriptions, including those for blood pressure and high cholesterol. Urine and blood samples were distributed to various laboratories at Vanderbilt University within four hours of collection. Virtually all respondents agreed to provide urine and blood samples with less than 1% refusing at the clinician's visit. However, data are missing for about 2% of respondents arising from difficulty in drawing sufficient blood or with specimen contamination.

Because the data collection represents a complex survey design, we constructed a sampling weight. The sampling weight accounts for non-response, non-cooperation, refusals, and non-contact across the screening *and* interviewing phases. Therefore, when applied, it increases confidence that the weighted data generalise to the black and white population aged 25–65 living in Davidson County, Tennessee during the time of the study. Accounting for success across the screening *and* interviewing phases, the American Association for Public Opinion Research (AAPOR) *Response Rate 1* equals 30.2, the *Cooperation Rate 1* equals 74.2, the *Refusal Rate 1* equals 9.4, and the *Contact Rate 1* equals 40.7. For more information regarding AAPOR rates and how they are calculated, see Response rates – an overview (n.d.).

Health status measures

Allostatic load

Allostatic load captures reactivity to social stress exposure and ensuing bodily wear-and-tear and consequent biochemical dysregulation (Dowd et al., 2009; McEwen, 1998, 2002; McEwen & Gianaros, 2010, 2011; McEwen & Seeman, 1999; McEwen & Stellar, 1993; McEwen & Wingfield, 2003). It represents an individual's location on a trajectory that arcs toward disease. Here we treat it as a measure of dysregulation across multiple, interdependent biochemical systems inside the body. Research suggests that allostatic load is a stronger predictor of disease than the individual biomarkers comprising it, when those individual biomarkers are considered one at a time (see Dowd et al., 2009; Karlamangla et al., 2012; McEwen, 1998, 2002; McEwen & Gianaros, 2010, 2011; McEwen & Seeman, 1999; McEwen & Stellar, 1993; McEwen & Wingfield, 2003; Seeman et al., 1997; Seeman et al., 2002).

Table 1. Cross-tabulations of allostatic load and self-report measures of health.

		Biochemical dysregulation according to allostatic load		
		No	Yes	
Excellent self-perceived health	True	283	134	417
	False	429	361	790
		712	495	1,207
	Design-based F (1, 249) = 17.688, $p < .000$			
Doctor-diagnosed health problems	None	676	441	1117
	One or more	36	54	90
		712	495	1,207
	Design-based F (1, 249) = 6.668, $p < .010$			
Bed days	None	636	429	1065
	One or more	76	66	142
		712	495	1,207
	Design-based F (1, 249) = 1.114, $p < .292$			
Activity limitations	None	601	351	952
	At least some	111	144	255
		712	495	1,207
	Design-based F (1, 249) = 22.955, $p < .000$			
Any of the above measures	No	249	110	359
	Yes	463	385	848
		712	495	1,207
	Design-based F (1, 249) = 16.366, $p < .000$			

We measure allostatic load using the following 10 components: (1) epinephrine, (2) norepinephrine, (3) cortisol, (4) dehydroepiandrosterone sulphate (DHEA-S), (5) systolic blood pressure, (6) diastolic blood pressure, (7) total cholesterol, (8) high density lipids (HDL), (9) glycated haemoglobin, and (10) waist-to-hip ratio. Allostatic load equals the sum of the number of components with scores falling above the third quartile (except for HDL and DHEA-S where the first quartile corresponds to poor health status). Note that individuals taking prescriptions to lower cholesterol are counted as having high total cholesterol and those taking prescriptions to lower blood pressure are counted as having high systolic and diastolic blood pressure. We did not assess other prescription medication use. We converted the count into a dichotomy where a positive score means respondents have at least four affirmative responses to the 10 components, or a 40% positive score on the available non-missing components, given that the respondent has valid data on at least five components. The number of missing cases for allostatic load was 31. A little more than 36% of respondents scored as dysregulated according to allostatic load (the unweighted percent was 41 – see Table 1). Analyses where allostatic load is constructed with different percentile cutoffs (80th or 90th) are available upon request. Results using more conservative cutoffs do not differ fundamentally from those presented here.

Self-perceived health

We measure self-perceived health with the following four questions: (1) 'You seem to get sick a little easier than other people (reverse coded).' (2) 'You are as healthy as anybody you know.' (3) 'You expect your health to get worse (reverse coded).' (4) 'In general, your health is excellent'. The response scale was 'definitely true', 'mostly true', 'don't know', 'mostly false', and 'definitely false'. Stating *definitely* or *mostly true* across all

four items represents excellent self-perceived health. This specification generated four missing cases. Approximately 64% of respondents scored as ill using this specification. Importantly, measures of self-perceived health predict mortality, morbidity, and physical disability (Farmer & Ferraro, 1997; Idler, 1992; Idler & Angel, 1990; Idler & Benyamini, 1997).

Doctor-diagnosed diseases

Many social scientific studies distinguish the healthy from the unhealthy by asking respondents to report whether a doctor has told them they have certain serious health problems or diseases (see Ferraro & Farmer, 1999; Hayward, Miles, Crimmins, & Yang, 2000; House et al., 1994; Ross & Wu, 1995; Sternthal, Slopen, & Williams, 2011). To capture doctor-diagnosed diseases, we coded any affirmative response to the following serious and *potentially fatal* health problems: (1) repeated pneumonia, (2) diabetes, (3) heart problems, or (4) stroke. In addition, to meet criteria, a respondent had to give affirmative responses to the following questions: (1) 'Did this start during the last 12 months?' and (2) 'Was this health problem diagnosed by a physician?' This approach generated two missing cases. Almost 7% of respondents reported at least one of the four doctor-diagnosed diseases in the last 12 months. Note that those diagnosed more than a year ago were grouped with those not having any of the conditions. This approach is conservative because it undercounts disease. We took this approach because biomarkers capture health at the very moment in time they are measured, thus there should be concordance with conditions diagnosed recently. Moreover, we are interested in addressing whether specific self-report health measures might stand in for biomarkers. As stated in the introduction, validity of doctor-diagnosed diseases depends upon several assumptions about access to and quality of health care.

Bed days

Meeting criteria for bed days requires reporting one or more days in response to two questions. The first question asked: 'During the past two weeks, how many days did your health keep you from work, housework, school or other activities?' If the answer was 'none', then bed days was zero. The second question asked: 'On how many days did you stay in bed for all or most of the day?' If the answer was at least one full day, then respondents met criteria for bed days (14% of respondents did). One respondent had missing data on bed days.

Activity limitations

This self-reported health measure asks respondents about difficulty in performing the following activities: (1) 'Reach up and get a 5 pound object (such as a bag of sugar) from just above your head'; (2) 'Bend down to pick up an object (like a piece of clothing) from the floor'; (3) 'Stoop or crouch down'; (4) 'Sit for more than two hours'; and (5) 'Walk a quarter of a mile'. The response scale was: 'easily', 'with some difficulty', 'with much difficulty', and 'unable to do'. Any difficulty (versus *easily*) on three or more activities represents the criteria for activity limitations. One respondent had missing data on activity limitations. Approximately 19% of respondents reported some difficulty (i.e. were positive cases). Measures capturing capacity to perform activities of daily living are used routinely with older populations or in rehabilitation settings (Brown & Turner, 2010; Jette, 1980; Katz, Downs, Cash, & Grotz, 1970).

Any of the above measures

About 69% of respondents in the NSAHS would be classified as ill at the time of the interview if we consider simultaneously those who meet case criteria for self-perceived health, doctor-diagnosed diseases, bed days, *or* activity limitations. The question of whether self-report health measures capture disease or feelings of being unwell cannot be answered definitively here. On the one hand, if biological makers of dysfunction correlate very strongly with the self-report health measures, then one might conclude that self-report health measures index disease. But on the other hand, if the concordance is weak, then it would be unclear whether these subjective indicators are tapping disease or feelings of being unwell. In addition, we recognise that this smallish group of self-report health measures is heterogeneous, but they tend to cover typical ways that subjective health is assessed in the literature.

Moderating variables

We explore whether race (*survey-adjusted proportions*: black [28%] vs. white [72%]), sex (*survey-adjusted proportions*: male [48%] vs. female [52%]), education (*survey-adjusted proportions*: no college degree [56%] vs. college degree [44%]), and past year depression (*survey-adjusted proportions*: no [89%] vs. yes [11%]) alter associations between allostatic load and the self-report health measures described just above.

Race was self-reported by respondents. Sex was interviewer-reported. Respondents stated the highest year of education they had attained. Past year depression was derived from the Composite International Diagnostic Interview (CIDI), which applies algorithms to closed-ended survey responses to mimic clinical assessment of psychiatric disorders. We examine race, sex, and education to determine whether the link between allostatic load and self-report health measures depends on social location. We examine past year depression because individuals with a negative psychological outlook may self-report feeling physically unwell (i.e. present state bias). Potential over-reporting among those experiencing depression would imply a stronger positive association between allostatic load and the self-report health measures. In contrast, those individuals not experiencing depression may be disinclined to self-report feeling ill, which would imply a weaker positive association between allostatic load and the self-report health measures.

Statistical analyses

Analyses were completed in Stata 13.1 and were adjusted for the NSAHS's complex survey design and sampling weight (using the *svy* commands). We ran a series of survey-adjusted tabulations and logistic regressions to estimate associations between allostatic load and the self-report health measures, which were all dichotomies. Overall, 45 cases were deleted because of missing values, thus the estimation sample size for results shown was 1207.

Results

Table 1 displays biochemical dysregulation according to allostatic load (*on the column*) against illness according self-report definitions (*on the rows*). Again, allostatic load captures whether respondents have at least 4 positive responses to the 10 components or

40% of the non-missing components (given valid data on at least 5 components). Unweighted table cell counts are shown. Weighted cell counts would be population totals and thus we do not show them. Survey-adjusted *joint probabilities* that generalise to the population of Davidson County, Tennessee are available upon request. Design-based test statistics are also reported in Table 1.

Considering excellent self-perceived health, 283 respondents were *healthy* whereas 361 were *unhealthy*. We found that 429 were *ill* – they reported less than excellent self-perceived health but failed to meet the allostatic load criteria for dysregulation. Similarly, 134 were *dysregulated* – they rated their health as excellent but met allostatic load criteria.

A similar pattern was observed with respect to doctor-diagnosed diseases. Although there was substantial concordance, after accounting for the marginal distributions, the ill and dysregulated were a non-trivial proportion (40%). In contrast, allostatic load and bed days did not significantly correlate – there was less concordance between them. Allostatic load associated significantly with activity limitations. Ill and dysregulated respondents represented a larger proportion when considering activity limitations than was the case for self-perceived health or doctor-diagnosed diseases. Tabulating allostatic load with meeting criteria on any of the four self-report measures revealed a significant association. Approximately 69% [249/(249 + 110)] of black and white adults healthy on any of the four self-report measures were healthy according to allostatic load. About 45% [385/(385 + 463)] of respondents unhealthy according to any of the self-report measures were also unhealthy according to allostatic load. Biological markers and self-report health measures, although positively and usually significantly related, appear to index distinct dimensions of health.

In survey-adjusted logistic regression models controlling for age (*survey-adjusted mean* = 44.27; *linearised SE* = 0.49), we now predict allostatic load using the self-report health measures to specify concordance in more detail (see Table 2). We then explore whether relationships between allostatic load and the self-report health measures depend upon race, sex, education, or past year depression. The full logistic regression results and goodness of fit statistics are available upon request.

In Table 2, each regression model (where a model corresponds to an odds ratio) includes only two predictors, age and a self-report health measure. Specifically, the first column arrays odds ratios for the full sample where allostatic load is predicted individually and in turn by each self-report health measure, controlling for age. The next two columns show odds ratios for black and white respondents, respectively, when allostatic load is predicted separately by race and each self-report health measure. The remainder of Table 2 replicates models by sex, education, and finally, past year depression. Table 3 displays *p*-values from statistical tests of the differences by race, sex, education, and past year depression.

Odds of being dysregulated according to allostatic load increased by a factor of 1.74 (95% CI: 1.259; 2.409) given less than excellent self-perceived health compared to excellent self-perceived health, net of age. We found that meeting criteria for doctor-diagnosed diseases (OR = 2.31; 95% CI: 1.207; 4.418) or activity limitations (OR = 1.78; 95% CI: 1.164; 2.717) were both positively predictive of allostatic load, controlling for age. In contrast, but consistent with results in Table 1, we gained little information about the distribution of allostatic load by considering bed days (95% CI: 0.647; 1.880). Finally, adjusting for age, odds of being unhealthy according to allostatic load increased by a factor of 1.70 (95%

Table 2. Predicting allostatic load using self-report measures: age-adjusted odds ratios ($n = 1207$).

	Biochemical dysregulation according to allostatic load								
	Full sample	Black respondents	White respondents[a]	Males	Females	No college degree	College degree	No past year depression	Past year depression
Self-perceived health	1.742***	1.464	1.912**	1.434	2.085**	1.474	2.222**	1.659**	2.798
Doctor-diagnosed diseases	2.309*	1.143	3.057*	1.649	3.217**	2.078*	2.533	2.363*	1.828
Bed days	1.103	2.186	.942	.912	1.338	1.063	1.081	1.243	0.414
Activity limitations	1.778**	1.254	1.988*	1.263	2.487**	1.408	1.896	1.776*	1.554
Any of the above measures	1.700**	1.654*	1.694*	1.321	2.213**	1.468	2.090**	1.559*	12.654**
Sample sizes	1207	601	606	566	641	770	437	1084	123

Notes: ORs estimated from design-based variance–covariance matrices that adjust for stratification, clustering, and the sampling weight. Presented are age-adjusted ORs for the full sample and then ORs by race, sex, education, and past year depression.

[a]The full sample size for this column was 1061 because 2 strata contained no subpopulation members (i.e. white respondents) and those strata were excluded.

*$p < .05$.

**$p < .01$.

***$p < .001$ (two-tailed tests).

Table 3. *P*-values from two-tailed tests of the differences in the age-adjusted odds ratios predicting allostatic load with self-report measures ($n = 1207$).

	Black vs. white respondents	Males vs. females	No college degree vs. college degree	No past year depression vs. past year depression
Self-perceived health	.441	.266	.249	.451
Doctor-diagnosed diseases	.126	.341	.739	.765
Bed days	.180	.353	.916	.114
Activity limitations	.198	.050	.421	.697
Any of the above measures	.942	.164	.316	.036

CI: 1.224; 2.359) if a respondent met criteria on any self-report health measure considered here.

With respect to the relative strength of self-report health measures in predicting allostatic load, doctor-diagnosed diseases has the largest odds ratio, followed by activity limitations, self-perceived health, any self-report health measure, and lastly, bed days. The greater predictive power of doctor-diagnosed diseases is logical given theorisation that allostatic load portends emergence of disease. However, confidence intervals for self-perceived health, doctor-diagnosed diseases, and activity limitations overlap, suggesting they have similar sampling distributions and arguably, effect sizes when predicting allostatic load.

The balance of Table 2 addresses whether we can be confident that odds ratios observed are invariant to race, sex, education, and past year depression. For example, controlling for age, self-perceived health, doctor-diagnosed diseases, and activity limitations were significantly predictive of allostatic load for white respondents but not for black respondents. In contrast, the composite indicator of ill on any self-report measure showed nearly identical odds ratios by race. However, none of the race differences were statistically significant (see Table 3). Analyses of sex differences reveal that relationships between allostatic load and the self-report health measures were more robust among females than males. However, only the odds ratios for activity limitations differed significantly by sex (see Table 3). Specifically, we found that allostatic load and activity limitations were more strongly linked among females compared to males. Despite variation in the odds ratios' magnitudes (except for bed days), earning a college degree did not moderate in a systematic way relationships between allostatic load and the self-report health measures.

Finally, we consider past year depression. Due in part to the larger sample size, odds ratios between allostatic load and self-perceived health, doctor-diagnosed diseases, and activity limitations were only statistically significant for respondents *not* experiencing past year depression (see Table 2). Inconsistent with the proposition that a negative psychological outlook creates over-reporting of illness, odds ratios from regressions of allostatic load on doctor-diagnosed diseases, bed days, and activity limitations were larger (but not significantly so) among those *not* experiencing past year depression. However, allostatic load and self-perceived health, and allostatic load and ill on any self-report health measure were more strongly, positively related among clinically depressed respondents (see Table 3). An alternative explanation for the latter pattern is that biomarkers are implicated in development of depression.

Discussion

This study described concordance between biological dysregulation and self-reported poor health. Findings suggest that there are meaningful aspects in subjective health uncaptured by dysregulation and, consequently, that biological markers do not obviate the need to ask people about their health-related perceptions and experiences. People's minds, thoughts, and social experiences matter when defining individual health status and population health. Yes, biological measures are more prestigious, and have the capacity to provide information beyond an individual's consciousness or symptom manifestation. However, based upon present results, one could argue that there are manifestations of health status in self-ratings, medical history, and activity limitations uncaptured by allostatic load. We conclude that the benefit of measuring health status using a combination of biological and self-report approaches might outweigh, *theoretically* (and perchance empirically), strengths each approach brings separately to the table. Findings of this study are consistent with conclusions from social scientific research suggesting that perceptions matter for health status (see Chiles, Lambert, & Hatch, 1999; Fadiman, 1997; Ferraro & Farmer, 1999; Jahoda, 1958; Keyes, 1998; Keyes, 2002; Kleinman, 1988; Krieger, 2005; Maier, Watkins, & Fleshner, 1994; Meador, 2005; Ray, 2004; Sternberg, 2001; Taylor et al., 1997).

Our findings confirm appreciable lack of concordance between allostatic load and commonly used self-report health measures. Discordance could happen for several reasons. First, as stated earlier, biomarkers capture health beyond a person's consciousness and indicate nascent disease states. Therefore, individuals may feel well and capable while experiencing biochemical dysregulation. Second, we know less regarding individual differences in responsiveness to social stress and inequality. It could be that certain types of people exhibit resilience in the face of social experiences that challenge their body's capacity to respond, whereas others advance more quickly on the trajectory toward disease manifestation. Third, there can be little doubt that the biological and sociological are interdependent. For example, social experiences alter our minds and thoughts, which in turn can influence biology and biochemistry (Kleinman, 1988; McEwen & Gianaros, 2010, 2011; Miller et al., 2011; Needham et al., 2012, 2013; Ray, 2004). Consequently, feeling capable and well may produce allostasis. Fourth, it could be that self-report health measures are not capturing health status as well as the literature would suggest. Maybe certain self-report health measures index high levels of self-awareness and self-worth and self-monitoring, rather than physiological functioning.

Limitations

One limitation of the present study is its age restriction. The sample design excluded persons who were younger than 25 or older than 65 during the screening phase. Thus, patterns reported here may only replicate among similar subpopulations outside Davidson County, Tennessee. An additional limitation regards the lack of standard guidelines for coding some health status outcomes. For example, in analyses not shown (but available upon request), we coded components of allostatic load according to cutoffs established in clinical medicine (Karlamangla et al., 2012). Results were not substantively different than those reported here. Another limitation is the study's cross-sectional design, which

does not allow detection of how allostatic load and self-report health measures vary together over time. Yet another limitation is the fact that we could not control for hypochondria or other abnormal behaviours that may have a biochemical basis and/or influence self-report health measures. Finally, Hispanics and other ethnic/racial groups, and immigrants were excluded from the NSAHS sampling frame and thus we cannot generalise to those populations.

Future directions

Based upon results of the present study, there are several next steps for future research. Investigators should treat categories (i.e. (1) healthy individuals, (2) unhealthy individuals, (3) ill individuals, and (4) dysregulated individuals) capturing concordance between biological markers and common self-report measures as a nominal dependent variable (see Figure 1). Would there be evidence that social stress exposure, for example, has a stronger effect when the ill and dysregulated are excluded from analyses, permitting a *purer* comparison of the healthy versus unhealthy? Or might low socio-economic status black men be overrepresented in the dysregulated or ill category? If so, such overrepresentation may help clarify the contribution of intersectionality theory to explaining health disparities. Intersectionality theory implies that statuses such as race, gender, social standing, and sexual orientation collide such that the effect of one is always and simultaneously contingent upon effects of the others.

We also advocate for examination of concordance between alternative biological markers and alternative self-report health measures. Are there *any* self-report health measures that show near perfect or perfect concordance with biomarkers? If so, researchers could comprehend which self-report measures best manifest biochemical dysregulation or physiological dysfunction. Given the dramatically different expense associated with self-report data collection and biological assay data collection and processing, respectively, scholars might develop proxy indicators of biochemical dysregulation that would allow them to analyse old self-report data in new ways. Related to this idea, biological markers might support or verify self-report health measures. For example, we found that poor self-perceived health and allostatic load were significantly and positively correlated. In addition, investigating other biological markers of dysregulation is necessary because results may differ from those reported in the present study. In the NSAHS data, for instance, allostatic load and leukocyte telomere length (assessed using monochrome multiplex quantitative polymerase chain reaction) are not significantly associated, hence it may be a distinct criterion variable, exhibiting different relationships with popular self-report health measures. Further, allostatic load is, by design and theoretically, based upon dichotomising multiple, continuous variables that index the performance of various biochemical bodily systems. There may be alternative approaches to coding allostatic load that better reveal the *range* of biological dysregulation.

Conclusion

On a health equity front, scholars should proceed with caution when describing health status or disparities using only one kind of indicator. Health is too complicated a concept to rely on one specification or one discipline's epistemology. Richer

operationalisation requires a unified (multidisciplinary) effort to map variation at the intersection of the body, mind, and social environment.

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