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Factors affecting workforce participation and healthy worker biases in U.S. women and men

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Abstract

Purpose—To investigate potential attenuation of healthy worker biases in populations in which healthy women of reproductive age opt out of the workforce to provide childcare.

Methods—We used 2013–2015 data from 120,928 U.S. women and men aged 22–44 years participating in the Gallup-Healthways Well-Being Index. We used logistic regression to estimate adjusted prevalence odds ratios (PORs) and 95% confidence intervals (CIs) for associations between health and workforce nonparticipation.

Results—Women and men reporting poor health were more likely to be out of the workforce than individuals reporting excellent health (POR: 3.7, 95% CI: 3.2–4.2; POR: 6.7, 95% CI: 5.7–7.8, respectively), suggesting potential for healthy worker bias. For women (P <.001) but not men (P = .30), the strength of this association was modified by number of children in the home: POR: 7.3 (95% CI: 5.8–9.1) for women with no children, decreasing to POR: 0.9 (95% CI: 0.6–1.5) for women with four or more children.

Conclusions—These results are consistent with attenuation of healthy worker biases when healthy women opt out of the workforce to provide childcare. Accordingly, we might expect the magnitude of these biases to vary with the proportion of women with differing numbers of children in the population.

Keywords

Bias (epidemiology); Healthy worker effect; Women

Introduction

Healthy worker biases encompass a variety of biases that arise in occupational epidemiology studies and result from differential entry into and exit from the workforce by factors related

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to health or disease risk [1]. Healthy hire bias and healthy worker survivor bias are the two types most often studied.

Healthy hire bias is confounding arising from differential entry into the workforce by healthy versus unhealthy individuals [2,3]. An example of a scenario resulting in healthy hire bias is comparison of risk (or prevalence) of disease in a worker population to risk in the general population: because healthier individuals are more likely to join the workforce than less healthy individuals, the risk of disease is lower in the working population than in the general population, which results in confounding when the two risks are compared [3].

Healthy worker survivor bias involves differential exit from the workforce by healthy versus unhealthy individuals. This bias takes the form of time-varying confounding affected by prior exposure and occurs when exposure causes less healthy individuals to leave the workforce, leaving healthier workers in the workforce [1,4]. Thus, a higher cumulative occupational exposure is accrued by the healthy individuals remaining in the workforce and a lower cumulative occupational exposure is accrued by the less healthy individuals who leave the workforce. The result is often a downward bias in the association between cumulative exposure and disease [1].

Poor physical health and mental health are important reasons why individuals leave or do not join the workforce, and these are the mechanisms through which healthy worker biases are thought to operate [2]. However, in many populations, substantial proportions of healthy women opt out of the workforce for reasons unrelated to health, such as to provide childcare [5]. Investigators have also found evidence suggestive of weaker healthy worker biases caused by healthy women leaving the workforce after marriage among U.S. white women in the 1960s and in a contemporary population of college-educated Japanese women [6,7].

The objective of this study was to explore relationships between health, workforce participation, and childcare in a contemporary U.S. population in which the number of children in the home might be a strong predictor of workforce nonparticipation for women, just as marriage was once a strong predictor of workforce nonparticipation in this population. We hypothesized healthy worker biases would be weaker among U.S. women with children compared with women without children and that a greater attenuation would be seen as the number of children in the home increased. However, we would not expect to see this effect for men, who do not traditionally leave the workforce to provide childcare. We used the magnitude of the association between workforce participation and self-reported health among women and men with differing numbers of children as a proxy for healthy worker bias.

Materials and methods

We included adult women and men participating in the Gallup-Healthways Well-Being Index (WBI) between January 2013 and October 2015 [8,9]. Approximately 175,000 adults (aged 18 years and over) from the 50 U.S. states and the District of Columbia were sampled yearly for the WBI using a cross-sectional telephone survey conducted in English or Spanish.

Participants were identified by dual-frame (landline and cell phone) random digit dialing from lists purchased from Survey Sampling International. The sample was stratified by time zone within U.S. census region and phone type. At least three attempts were made to contact the household. For landlines, the adult household member with the next upcoming birthday was selected to participate. For cell phones, the person answering the phone was selected (if eligible) because the device is treated as a personal device. Since the WBI began in 2008, an average of 74% of eligible respondents reached have completed the interview (the overall contact rate [persons reached out of all active or inactive numbers called] was 9%). Samples were weighted to account for selection probability, nonresponse, and households with both cell phones and landlines being present in both sampling frames. In addition, samples were weighted by demographic variables to match distributions expected based on the most recent Current Population Survey (gender, age, race, ethnicity, education, region, population density, phone status) [9]. Participants provided verbal agreement to participate in the telephone survey.

Our primary association of interest was between self-reported health (exposure) and workforce nonparticipation (outcome), the magnitude of which was used as a proxy for the magnitude of healthy worker bias. For this to be valid, we made the following assumptions. First, we assumed that healthy worker bias had the structure of confounding (either time invariant or time varying affected by prior exposure), in which health affected both an occupational exposure (through workforce participation) and a hypothetical disease outcome (corresponding directed acyclic graphs are provided in eAppendix Fig. A1). Second, we assumed that the association between health and the hypothetical disease outcome was constant, so that the stronger the association between health and workforce participation, the stronger the likely effect of healthy worker bias.

We restricted our analysis to adults aged 22–44 years to focus on the time when reproductive-aged women might be raising young children, to exclude age groups in which substantial proportions of respondents are out of the workforce because they are in school (ages 18–21 years), and to reduce the likelihood that workforce nonparticipation would be driven by retirement or work-related chronic disease, which might be more prevalent in older populations.

We used self-rated health as our measure of general health status based on the question, “Would you say your own health, in general, is excellent, very good, good, fair, or poor?”.

We categorized WBI participants as in the workforce (working for an employer, being self-employed fulltime or part-time, or being unemployed and looking for work) or out of the workforce (unemployed and not looking for work) at the time of the survey. To determine employment status, participants were asked: “Thinking about your work situation over the past 7 days, have you been employed by an employer—even minimally like for an hour or more—from whom you receive money or goods?” and “Again thinking about the last 7 days, were you self-employed, even minimally like for an hour or more? This means working for yourself, freelancing, or doing contract work or working for your own or you family’s business?”. To determine if participants who did not report a job were actively looking for work, they were asked: “In the past four weeks, have you actively been looking for employment? ‘Actively looking’ means applying for jobs, searching for jobs, and the like”.

Additional variables of interest related to self-reported health and workforce nonparticipation included age (22–29, 30–34, 35–39, 40–44 years), race/ethnicity (non-Hispanic white, non-Hispanic black, Hispanic, other), educational attainment (less than high school, high school or equivalent, some college or vocational training, college graduate, graduate work or degree), and number of children aged less than 18 years in the home (0, 1, 2, 3, ≥4).

We first investigated which of our variables of interest were associated with the outcome (workforce nonparticipation) by using multivariable models to examine associations between these variables (including self-reported health, the exposure) and workforce nonparticipation. Covariate choice for multivariable models was guided by directed acyclic graphs (eAppendix Fig. A2) [10]. We adjusted the models for age and race/ethnicity when education was the variable of interest and adjusted for age, race/ethnicity, and education in models for self-rated health and number of children. Models in which age or race/ethnicity was the variable of interest remained unadjusted.

A second set of models was created to see how presence of children in the home affected the strength of the main association of interest between self-reported health and workforce nonparticipation. First, we included interaction terms between number of children in the home and self-reported health to assess departure from multiplicative interaction. Then, we used stratified analyses to see how the magnitude of the association varied.

We used survey procedures for logistic regression to estimate prevalence odds ratios (PORs) and 95% confidence intervals (CIs) for associations between variables in SAS version 9.4 (Cary, NC), accounting for the sampling weights. Linear tests for trend were used to identify potential dose-response relationships, using the variable itself for continuous variables and ordinal scores for categorical variables. Results for this test were presented as both *P*-values and POR and 95% CI.

We excluded individuals with missing data for any variables of interest from all analyses. Of 55,262 participating women and 70,215 men aged 22–44 years, we excluded the following number of participants for missing data on the following variables: work-force participation (1 woman), self-reported health (30 women, 82 men), race/ethnicity (1273 women, 2088 men), educational attainment (338 women, 397 men), and number of children in the home (99 women, 241 men). Overall, 1741 (3%) women and 2808 (4%) men were excluded from the analysis.

Results

Among the 53,521 women and 67,407 men in the analysis, 24% of women and 10% of men (weighted prevalence) were not participating in the workforce.

Characteristics of women and men in and out of the workforce are shown in Table 1. Women aged 30 years and above were slightly more likely to be out of the workforce than women in their 20s; for men, there was no difference by age. For women, workforce nonparticipation was higher among Hispanic women (POR: 1.7, 95% CI: 1.6–1.8) and women of "other" races (POR: 1.3, 95% CI: 1.1–1.4), compared with non-Hispanic white women. For men, workforce nonparticipation was higher among non-Hispanic black men (POR: 2.1, 95% CI: 1.9–2.3), Hispanic men (POR: 1.5, 95% CI: 1.4–1.7), and men of "other" races (POR: 1.8, 95% CI: 1.6–2.1) compared with non-Hispanic white men. Education was strongly associated with workforce nonparticipation in both women and men, with greater educational attainment associated with increasing workforce participation (P for trend <.001 for both men and women). Having children aged less than 18 years in the home was associated with workforce nonparticipation for women (POR: 1.6, 95% CI: 1.5–1.6 for any vs. no children); conversely, men were more likely to participate in the workforce when there were children in the home (POR: 0.6, 95% CI: 0.5–0.6 for any vs. no children). Likelihood of being out of the workforce increased for women as the number of children in the home increased; for men, it remained constant.

Both women and men out of the workforce reported poorer health than those in the workforce, with the association weaker for women (POR: 3.7, 95% CI: 3.2–4.2 poor vs. excellent health) than for men (POR: 6.7, 95% CI: 5.7–7.7) (Table 1). When interaction terms between health and number of children were entered into the model, there was evidence of interaction for women ($P < .001$) but not for men ($P = .30$). After stratifying the health and workforce nonparticipation results by number of children aged less than 18 years in the home (Table 2), the association attenuated and then disappeared for women as the number of children in the home increased. For women with poor compared to excellent self-rated health, the POR was 7.3 (95% CI: 5.8–9.1) for women with no children in the home and 0.9 (95% CI: 0.6–1.5) for women with four or more children in the home. In contrast, the association remained strong (PORs between 5.9 and 9.9) for men, regardless of the number of children in the home. The sample sizes and proportion of individuals out of the workforce for each population in this analysis are presented in eAppendix Table A1.

Discussion

Self-reported health and workforce participation were associated among U.S. women and men aged 22–44 years, with individuals in poorer health less likely to participate in the workforce than those in excellent health. Previous studies have consistently reported poorer health among unemployed individuals compared to employed individuals; however, individuals out of the workforce (i.e., not actively seeking employment) were frequently excluded from these studies [11–13]. A study from England showed that women out of the workforce because they were caring for family were more likely to report poor health than employed women [14]. This association between health and workforce participation suggests potential for healthy worker bias to occur, given the structures of healthy worker biases we assumed. However, our finding that this association was attenuated among women with increasing numbers of children aged less than 18 years in the home indicates the potential for a lesser impact of healthy worker bias when women leave the workforce for nonhealth reasons, such as providing childcare, diluting the effect of healthy worker bias.

Childcare is a major driver of workforce nonparticipation among women. Previous research (using data from 1979 to 1994) showed that presence of preschool-aged children in the home was a strong predictor of workforce nonparticipation among women [5]. In 2012, an estimated 29% of U.S. women with children aged less than 18 years in the home did not work at a job in the past year, similar to the estimate of 28% in our data [15]. We hypothesized that we would observe a weakened association between self-reported health and workforce participation as the number of children in the home increased (i.e., greater likelihood of opting out of the workforce for reasons aside from health), which is what we observed. When there were no children in the home (i.e., no women opting out of the workforce to provide childcare), the magnitudes of the association between self-reported health and workforce participation were similar for women and men, suggesting that in the absence of childcare responsibilities, health might be a similarly important factor in workforce participation between the two genders.

Although our example focused on childcare as a counteracting force to healthy worker biases in female populations, any factor that causes substantial proportions of healthy individuals (female or male) to opt out of the workforce could have a similar effect. In the 1960s, a stronger association between self-reported health and workforce exit was reported among unmarried white women in the United States than among married white women, perhaps due to societal pressures at the time that caused married women to opt out of the workforce [6]. Single parenthood, providing eldercare, or living in an area with few economic opportunities are examples of additional variables that might drive healthy individuals out of the workforce and attenuate the health-workforce participation relationship. As a result, we might expect variable impact of healthy worker bias in the presence or absence of social, cultural, or economic forces that are strong drivers of workforce participation.

There are methods available to account for healthy worker biases in study design and analysis [1,16]. However, in studies in which healthy worker biases cannot be well accounted for (e.g., some occupational cohorts), making valid comparisons of results between studies might be challenging, given the observations of this and other studies suggesting that the magnitude of bias might vary by population characteristics [6,7].

Throughout the article, we referred to healthy worker biases without specifying if we meant healthy hire bias (differential entry into the workforce) or healthy worker survivor bias (differential exit from the workforce). This was because, in our cross-sectional study, it was not possible to determine the temporality of the association (i.e., if workforce nonparticipation was due to health limitations that precluded entrance into the workforce or health limitations that had prompted exit from the workforce).

We used self-reported health to represent the difference in disease risk between individuals in and out of the workforce, but we recognize that this might not be as equally a strong predictor of all health outcomes (e.g., self-reported health might be associated more strongly with chronic conditions than occupational injury) and that “health” might be defined differently by different respondents [17]. Our numeric results therefore serve only as examples illustrating how the potential effect of healthy worker biases might vary across populations depending on population characteristics (here, number of children in the home) and might not generalize to all exposures, health outcomes, or populations.

The WBI data set provided the unique advantage of having a large number of participants recruited over a short time period. This provided adequate power for studying the intersection of fairly uncommon events (e.g., individuals with ≥4 children who reported poor health). Because the data were collected in a short time period, in the analysis, we did not have to account for time trends in variables such as cultural shifts in child-rearing expectations, number of children per household, and availability of flexible or alternative work schedules that have occurred over the past several decades and that might affect workforce participation, particularly among women.

However, this data set had limitations. The low contact rate of the WBI (9% of all numbers called) could have affected generalizability of results, although the participation rate among eligible participants reached was fairly high (74%), and the data were weighted to account for nonresponse and sociodemographic characteristics of respondents. A previous comparison of WBI participant characteristics to nationally representative data showed that WBI participants were slightly older, less likely to be members of racial/ethnic minorities, and more likely to have higher educational attainment [8]. The data set also did not include information on the ages of children in the home. Because having preschool-aged children in the home is a stronger driver of workforce participation than having older children at home, restricting our analysis to presence of younger children in the home might have strengthened the associations we observed [5].

In this study, we found that healthy worker biases might be attenuated in populations in which a substantial number of healthy women opt out of the workforce to provide childcare. Accordingly, if healthy worker biases cannot be accounted for through study design or analysis, we might expect the results of epidemiologic studies to be variably affected by healthy worker biases depending on the prevalence of women, the average number of children per woman, or the prevalence of other factors that might affect work-force participation in the worker population.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Table 1

Characteristics of women and men aged 22–44 years in and out of the workforce—Gallup-Healthways Well-Being Index, 2013–2015

	Women, N = 53,521		Men, N = 67,407		Women	Men
	n (Unweighted)	% Out of workforce (row %, weighted)	*n* (Unweighted)	% Out of workforce (row %, weighted)	Out versus in workforce adjusted POR (95% CI)*	
Age category (y)						
22–29	17,188	22	23,277	10	1.0 (Reference)	1.0 (Reference)
30–34	11,806	25	14,803	9	1.2 (1.1–1.2)	0.9 (0.8–1.0)
35–39	11,539	27	13,981	9	1.3 (1.2–1.4)	0.9 (0.8–1.0)
40–44	12,988	25	15,346	10	1.2 (1.1–1.3)	1.0 (0.9–1.1)
P for linear trend					P < .001	P = .27
Race/ethnicity						
Non-Hispanic white	33,889	22	45,480	8	1.0 (Reference)	1.0 (Reference)
Non-Hispanic black	7465	20	6842	15	0.9 (0.8–1.0)	2.1 (1.9–2.3)
Hispanic	9165	32	10,501	12	1.7 (1.6–1.8)	1.5 (1.4–1.7)
Other	3002	26	4584	14	1.3 (1.1–1.4)	1.8 (1.6–2.1)
Educational attainment						
Less than high school	3248	47	3785	17	1.7 (1.6–1.9)	1.5 (1.3–1.6)
High school or equivalent	8262	33	13,193	13	1.0 (Reference)	1.0 (Reference)
Some college/vocational	15,433	23	19,693	9	0.6 (0.6–0.7)	0.7 (0.6–0.8)
College graduate	15,785	15	19,577	5	0.4 (0.3–0.4)	0.4 (0.3–0.4)
Graduate work or degree	10,793	12	11,159	5	0.3 (0.2–0.3)	0.4 (0.3–0.4)
P for linear trend					P < .001	P < .001
Children aged <18 years†						
No	19,104	17	32,640	12	1.0 (Reference)	1.0 (Reference)
Yes	34,417	28	34,767	8	1.6 (1.5–1.6)	0.6 (0.5–0.6)
Number of children†						
0	19,104	17	32,640	12	1.0 (Reference)	1.0 (Reference)
1	11,209	23	11,483	8	1.2 (1.2–1.3)	0.6 (0.5–0.7)
2	13,248	27	13,674	7	1.6 (1.4–1.7)	0.6 (0.5–0.6)
3	6303	33	6178	9	1.8 (1.7–2.0)	0.6 (0.5–0.7)

	Women, N = 53,521		Men, N = 67,407		Women	Men
	n (Unweighted)	% Out of workforce (row %, weighted)	*n* (Unweighted)	% Out of workforce (row %, weighted)	Out versus in workforce adjusted POR (95% CI)*	
≥4	3657	39	3432	9	2.3 (2.1–2.5)	0.6 (0.5–0.7)
P for linear trend					*P* < .001	*P* < .001
Self-rated health						
Excellent	12,456	19	15,761	7	1.0 (Reference)	1.0 (Reference)
Very good	17,912	18	22,385	7	0.9 (0.8–0.9)	1.0 (0.9–1.1)
Good	15,214	25	20,223	9	1.1 (1.0–1.2)	1.2 (1.1–1.3)
Fair	6369	35	7535	17	1.5 (1.3–1.6)	2.1 (1.9–2.3)
Poor	1570	57	1493	39	3.7 (3.2–4.2)	6.7 (5.7–7.8)
P for linear trend					*P* < .001	*P* < .001

n = number of participants.

*Models for age and race/ethnicity are unadjusted. Model for educational attainment is adjusted for age category and race/ethnicity. All other models are adjusted for age category, race/ethnicity, and education.

†Number of children in household aged less than 18 years.

Table 2

Health and nonparticipation in the workforce, women and men aged 22–44 years, by number of children aged less than 18 years in the household—Gallup-Healthways Well-Being Index, 2013–2015

Self-rated health	Adjusted prevalence odds ratio (95% confidence interval)*				
	0 Children	**1 Child**	**2 Children**	**3 Children**	**≥4 Children**
Women					
Excellent	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Very good	1.0 (0.8–1.1)	0.9 (0.8–1.0)	0.9 (0.8–1.0)	1.0 (0.8–1.1)	0.6 (0.5–0.8)
Good	1.3 (1.2–1.6)	1.2 (1.1–1.5)	1.1 (0.9–1.2)	1.1 (0.9–1.3)	0.8 (0.6–1.0)
Fair	2.3 (1.9–2.7)	1.8 (1.5–2.1)	1.4 (1.1–1.6)	1.2 (1.0–1.5)	0.9 (0.7–1.2)
Poor	7.3 (5.8–9.1)	6.2 (4.7–8.3)	3.2 (2.4–4.3)	1.9 (1.3–2.8)	0.9 (0.6–1.5)
P for linear trend	$P < .001$	$P < .001$	$P < .001$	$P = .002$	$P = .95$
Men					
Excellent	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)	1.0 (Ref)
Very good	1.0 (0.9–1.2)	0.9 (0.7–1.1)	0.9 (0.7–1.2)	1.0 (0.7–1.4)	1.0 (0.6–1.6)
Good	1.2 (1.1–1.4)	1.2 (0.9–1.6)	1.2 (0.9–1.5)	1.2 (0.8–1.7)	1.4 (0.9–2.2)
Fair	2.1 (1.8–2.4)	2.1 (1.6–2.9)	1.9 (1.4–2.5)	2.4 (1.6–3.6)	1.4 (0.8–2.3)
Poor	6.1 (5.0–7.5)	6.6 (4.5–9.7)	5.9 (4.0–8.7)	9.9 (6.0–16.5)	6.1 (3.2–11.6)
P for linear trend	$P < .001$	$P < .001$	$P < .001$	$P < .001$	$P < .001$

* Adjusted for age, race/ethnicity, and education.