UC Irvine
UC Irvine Previously Published Works

Title
Greater ability to express positive emotion is associated with lower projected cardiovascular disease risk

Permalink
https://escholarship.org/uc/item/28n486fh

Journal
Journal of Behavioral Medicine, 40(6)

ISSN
0160-7715

Authors
Tuck, Natalie L
Adams, Kathryn S
Pressman, Sarah D
et al.

Publication Date
2017-12-01

DOI
10.1007/s10865-017-9852-0

Peer reviewed

CrossMark

Greater ability to express positive emotion is associated with lower projected cardiovascular disease risk

Natalie L. Tuck[1] · Kathryn S. Adams[2] · Sarah D. Pressman[3] · Nathan S. Consedine[1]

Abstract Positive emotion is associated with lower cardiovascular disease (CVD) risk, yet some mechanisms remain unclear. One potential pathway is via emotional competencies/skills. The present study tests whether the ability to facially express positive emotion is associated with CVD risk scores, while controlling for potential confounds and testing for sex moderation. Eighty-two men and women underwent blood draws before completing self-report assessments and a performance test of expressive skill. Positive expressions were scored for degree of 'happiness' using expression coding software. CVD risk scores were calculated using established algorithms based on biological, demographic, and behavioral risk factors. Linear regressions revealed a main effect for skill, with skill in expressing positive emotion associated with lower CVD risk scores. Analyses also revealed a sex-by-skill interaction whereby links between expressive skill and CVD risk scores were stronger among men. Objective tests of expressive skill have methodological advantages, appear to have links to physical health, and offer a novel avenue for research and intervention.

Keywords Emotion · Emotion regulation · Expressive skill · Cardiovascular disease · Health

✉ Nathan S. Consedine
n.consedine@auckland.ac.nz

Natalie L. Tuck
natalie.tuck@auckland.ac.nz

[1] Department of Psychological Medicine, University of Auckland, Auckland, New Zealand

[2] School of Medicine, University of Auckland, Auckland, New Zealand

[3] Department of Psychology and Social Behavior, University of California, Irvine, CA, USA

Introduction

Positive emotionality appears to predict better health and lower future disease risk (Chida & Steptoe, 2008; Howell et al., 2007; Pressman & Cohen, 2005). Although work has largely focused on positive emotional *experience*, evidence suggests that the *expression* of positive emotion may also have links with health, including reduced cardiovascular disease (CVD) risk (Davidson et al., 2010; Hayashi et al., 2016). However, whether individual differences in the *ability* to express positive emotions are also associated with cardiac outcomes remains unknown. Therefore, the present study tests whether objective measures of the ability to *deliberately* express positive emotion predicts CVD risk scores.

Although facial expressions can be spontaneous signals of internal experience, expressions are also *intentionally* adjusted in a manner that regulates autonomic and affective processes, and influences social interactions (Kraft & Pressman, 2012; Owren & Bachorowski, 2001; Soussignan, 2002). Greater *skill* in deliberately expressing emotions may thus confer an adaptive advantage (Consedine et al., 2002) and, although numerous expressions might predict outcomes, evidence of links between positive expressivity and lower cardiac risk (Davidson et al., 2010), suggest that an initial focus on the ability to express *positive* emotion is warranted.

Skill in expressing positive emotions may predict cardiac risk via several pathways. First, positive expressions are thought to have evolved to signal a willingness to interact and co-operate (Owren & Bachorowski, 2001), potentially increasing social resources and/or reducing the risk of loneliness and isolation, both established CVD risk factors (Valtorta et al., 2016). Second, the ability to deliberately express positive emotion may reflect differ-

Springer

ences in general regulatory capacities (Soussignan, 2002), which in turn predict lower cardiac risk (Potijk et al., 2016). Finally, deliberate smiles may reduce risk via directly lowering physiological arousal (e.g. Fredrickson, 2013; Kraft & Pressman, 2012; Tuck et al., 2016b).

Although links between expressive skill and projected CVD risk have not been systematically examined, the ability to signal positive emotion has been associated with better perceived health, lower concentrations of inflammatory markers (Tuck et al., 2016a), and higher heart rate variability (Tuck et al., 2016b). Other work has shown that smile intensity prospectively predicts personality, marital stability, and mortality (Abel & Kruger, 2010; Harker & Keltner, 2001) and, although such data are typically interpreted as reflecting differences in trait positive affect (PA), differences in smile intensity may reflect differences in expressive capabilities. However, although expressive skill predicts more adaptive patterns of physical and emotional responding (Tuck et al., 2016a), it is unknown whether the *ability* to signal positive emotion will also predict clinically relevant health metrics.

Consequently, the present report assessed whether the ability to express positive emotion was associated with CVD risk scores. In contrast to cardiac morbidity and mortality, CVD risk scores use validated algorithms to predict risk of *future* cardiac events in non-clinical samples, using traditional biological, demographic and behavioral risk factors. Such measures reliably predict future incidence of cardiac outcomes, including coronary death, myocardial infarction, and heart failure (D'Agostino et al., 2008). Although *trait* emotion regulation has been associated with estimates of projected CVD risk (Appleton & Kubzansky, 2014), the possibility that expressive regulatory skills will also be associated with cardiac risk scores has not been tested.

Nonetheless, our expectation was that greater ability would be associated with a lower projected CVD risk. Furthermore, given evidence that links between psychosocial parameters and disease risk may be more apparent among men (Yang et al., 2013), and to clarify whether potential links can be attributed to underlying emotional and/or social factors, the current study investigated whether links between positive expressive skill (PES) and three CVD risk scores were comparable across men and women, and while controlling for trait PA, depressive symptoms, and loneliness.

Methods

Participants

An a priori power analysis using G-Power software was run based on $\alpha = .05$ and power $= 80\%$ (Faul et al., 2009).

Although the novelty of the predictor variables meant that there was little empirical guidance regarding effect sizes, an effect size of $R^2 = .15$ was previously reported in links between positive expressive skill and the inflammatory marker interferon gamma (IFN-γ) (Tuck et al., 2016a). Thus, power analyses using a slightly more conservative range of effect sizes ($R^2 = 0.10$–0.15) indicated that a sample size of N $= 67$–103 should provide 80% power.

Ninety-eight participants were recruited between November 2015 and January 2016 for a cross sectional study titled 'Emotions and Health' in Auckland, New Zealand, via university and hospital staff mailing lists and word of mouth. Advertisements invited participants aged 30 and over to "take part in a study examining how social and emotional factors are related to health outcomes such as cardiovascular disease risk." Photographs of 15 participants were not of sufficient quality to be analyzed, and venipuncture could not be completed for one participant, resulting in a final sample of 82 participants with complete data (see Table 1).

Procedure

Following informed consent, participants completed online measures of demographics, health, PA, depression, loneliness, and emotional intelligence (EI) before attending a laboratory session at a clinical research center. Upon arrival, height and weight were measured, followed by a blood draw (details below), before participants completed assessments of social skills. Participants were then fitted with a Polar watch heart rate monitor and chest strap (model RS800CX), before completing an orthostatic heart rate variability (HRV) challenge. Blood pressure was recorded twice (details below) followed by a performance-based assessment of expressive skill. For this, participants were seated at a computer and informed that 10 emotion terms would appear on the monitor. As each term appeared, participants were instructed to pose a genuine and accurate expression of that emotion as rapidly as possible then press the spacebar to record a digital photograph. Resting heart rate (HR) was recorded for a further 3 min. Following this, participants reported how much effort they put into producing target expressions before they were thanked and given a $40 voucher. Analysis of HRV/HR, EI and social skills are also not included in the present report.

Measures

Cardiac risk scores

To account for differences in the relative weighting of CVD risk factors due to nationality (e.g. Jackson, 2000), whilst ensuring that findings can be interpreted in the

Table 1 Sample characteristics; stratified by sex with Students *t* and Chi square tests of significant differences

	Men (N = 20)			Women (N = 62)			Test statistic	*p*
	Count (%)	Mean (SD)	Range	Count (%)	Mean (SD)	Range		
Smoker[a]	1 (5%)	–	–	1 (1.5%)	–	–	–	–
Diabetic[a]	1 (5%)	–	–	1 (1.5%)	–	–	–	–
Taking BP medication[b]	2 (10%)	–	–	8 (13%)	–	–	0.12	0.73
Not-white[b]	6 (30%)	–	–	16 (26%)	–	–	0.14	0.71
Age[c]	–	49.95 (15.50)	31.10–75.14	–	51.50 (14.25)	30.05–76.39	−0.41	0.68
Cholesterol (mmol/L)[c]	–	5.06 (1.10)	3.30–8.10	–	5.34 (1.19)	3.30–8.00	−.96	0.34
HDL cholesterol (mmol/L)[c]	–	1.42 (0.41)	0.90–2.50	–	1.75 (0.53)	0.80–3.60	−2.61	0.01
HDL ratio[c]	–	3.80 (1.19)	2.30–6.20	–	3.29 (1.33)	1.50–8.10	1.54	0.13
SBP (mmHg)[c]	–	124.59 (11.18)	107.30–144.00	–	118.25 (12.96)	99.00–147.00	1.96	0.05
Framingham risk[c,d]	–	−1.49 (2.93)	−4.61–2.00	–	−1.76 (2.82)	−4.61 to 2.00	0.37	0.71
NZ risk[c,d]	–	1.36 (1.12)	0.22–2.82	–	0.92 (0.83)	0.22–2.82	1.87	0.12
ASCVD[c,d]	–	−3.76 (1.90)	−7.05 to −1.64	–	−4.40 (1.71)	−8.08 to −1.64	1.40	0.17
Positive expressive skill[c]	–	0.36 (0.38)	0.00–0.98	–	0.45 (0.37)	0.00–0.99	−0.95	0.34
Trait positive affect[c]	–	3.36 (0.61)	2.22–4.44	–	3.49 (0.43)	2.33–4.44	−1.05	0.30
Depressive symptoms[c]	–	11.70 (9.60)	0.00–36.00	–	9.89 (7.00)	0.00–31.00	−0.17	0.86
UCLA loneliness[c]	–	18.15 (10.78)	0.00–45.00	–	17.50 (9.12)	2.00–41.00	0.27	0.79

[a] Test statistic not applicable on counts of 1

[b] Test statistic = Chi squared (χ^2)

[c] Test statistic = Students *t* test

[d] Risk scores are log transformed and windsorized

context of prior work (e.g. Appleton et al., 2013; Haynes et al., 1980), three similar but distinct measures of CVD risk were calculated.

The Framingham Heart Study (FHS) 10-year prognostic algorithm

The Framingham algorithm measures projected 10-year risk of CVD events using gender-specific Cox proportional-hazard regression models that incorporate age, total cholesterol, high-density lipoprotein (HDL) cholesterol, systolic blood pressure (SBP), antihypertensive medication use, smoking and diabetes status (D'Agostino et al., 2008). The Framingham algorithm has good predictive validity for CVD events including coronary heart disease, stroke, peripheral artery disease, or heart failure (D'Agostino et al., 2008), with estimated population risk strongly associated (goodness of fit: $R^2 = 0.84$) and in agreement with observed risks ($h = 0.84$; 95% CI 0.41–1.26) (Eichler et al., 2007). Although there is debate regarding the generalizability of the Framingham algorithm among diverse groups (Goff et al., 2013), risk scores are generally well calibrated to predict coronary events and the Framingham

risk algorithm is frequently used as an assessment tool in clinical guidelines (Wood et al., 2005). Outliers were identified and winsorized using the outlier labelling rule; $F_U + 1.5(F_U − F_L)$ and log transformations were applied to correct for positive skew (Table 1).

New Zealand 5-year CVD risk

NZ specific 5-year CVD risk scores were calculated using local clinical guidelines (Jackson, 2000). Risk scores are derived from charts which consist of a matrix of cells. Each row relates to bands of SBP, and each column relates to total-HDL cholesterol ratio. Each cell corresponds to projected 5-year CVD risk in 5% increments ranging from <5%–>30%, with different matrices for the presence/absence of diabetes, smoking, gender, and for each decade of age from 30 to 70 years. NZ risk scores have good sensitivity and specificity (Jones et al., 2001). Participants were allocated a risk score based on the mid-point of their assigned risk category, i.e. if categorized as 15–20% risk, they were given a score of 17.5%. As with the Framingham scores, outliers were identified and winsorized and log transformations applied (Table 1).

Ten-year atherosclerotic cardiovascular disease (ASCVD) risk scores

The American College of Cardiology (ACC)/American Heart Association (AHA) Pooled Cohort Risk Equation for estimating atherosclerotic cardiovascular disease (ASCVD) (Goff et al., 2013) was developed to improve generalizability among non-white samples and to capture risk of both cardiac events and stroke. ASCVD scores are based on age, sex, cholesterol, SBP, smoking and diabetes status. Again, outliers were winsorized and log transformations applied (Table 1).

Demographic and bio-behavioral components of projected CVD risk calculations

Cholesterol Immediately following blood draws, a 5 mL vacutainer of plain blood was transported to the local hospital laboratory facility (LabPlus, Auckland City Hospital) for analysis of total cholesterol, HDL cholesterol, low density lipoprotein (LDL) cholesterol and triglycerides in non-fasting plasma. Analyses were initiated within 45 min of blood draws and completed using standard hospital procedures (Table 1).

Systolic blood pressure (SBP) Participants sat quietly for 3 min before blood pressure readings were collected using an automated Dinamap V100 vital signs monitor. Blood pressure was measured using the right arm, which was placed on a desk, at approximately heart height. SBP was recoded as the average of two consecutive readings (Table 1).

Self-reported risk measures Age, sex, antihypertensive medication use, physician diagnosed diabetes, and current smoking status were self-reported (Table 1).

Emotional and social covariates

Positive affect (PA)

The 36-item, trait Differential Emotions Scale Version-IV (DES-IV) (Izard et al., 1993) was used to assess trait PA. Respondents reported their day to day experiences on items such as; "how often do you feel happy" using 5-point scales ranging from rarely/never, to very often. The DES-IV has good construct validity and has been used in a range of ages in community and clinical samples (Boyle et al., 2015). Scores from the positive emotion subscales were aggregated to generate a total PA score ($\alpha = .78$) (Table 1).

Depressive symptoms

The Centre for Epidemiologic Studies Depression Scale (CES-D) is a 20-item self-reported measure of depressive symptoms designed to be used in the general population (Radloff, 1977). The CES-D has good reliability and validity (Orme et al., 1986), in the present study $\alpha = .85$ (Table 1).

Loneliness

The University of California, Los Angeles (UCLA) Loneliness Scale (Version 3) is a 20-item scale assessing subjective loneliness and isolation (Russell, 1996). Participants rate items such as "How often do you feel close to people?" (reverse scored) on a scale from 1 (Never) to 4 (Often). The scale has good reliability and validity (Russell, 1996). In the present study $\alpha = .91$ (Table 1).

Expressive skill

Participants deliberately facially expressed 10 basic emotions (happiness, sadness, anger, disgust, interest, fear, guilt, embarrassment, shame and contempt) as quickly and accurately as possible. A TrueVision HD integrated webcam recorded expressions as jpg files (mean size = 24.67 kb). Happy expressions were scored using Noldus FaceReader™ software version 5.0 (Loijens et al., 2014), which scores expressivity based on facial muscle contractions, assigning a value between 0 and 1 for each of six discrete emotions (happiness, sadness, surprise, anger, fear, disgust) as well as neutral. A perfect 1, for happiness, for example, would indicate a large Duchenne smile defined by strong movement of the facial action units corresponding to the orbicularis oculi and the zygomatic major, indicative of sincere positive emotion. FaceReader has good construct validity and accuracy when compared with manually coded scores (Cohen et al., 2013; Lewinski, 2015). Skill in expressing positive emotion was scored by dividing the 'happy' score by the sum of the total expressivity in the 'happy' photograph. This generates positive expressivity scores that are independent of general or trait expressivity (Table 1). Note that all results were the same when the raw score 'happy' score was used without adjusting for general expressivity.

Effort

To ensure participants attempted to generate accurate expressions during the photo task they used a scale from 1 (I did not try at all) to 7 (I tried really hard) to indicate their

Table 2 Zero order correlations between trait affect, positive expressive skill, sex, and CVD risk variables

	1	2	3	4	5	6	7
1. Sex (0 = male)[a]							
2. Framingham 10 year risk[b]	−.05						
3. NZ 5 year risk[b]	−.19[t]	.86***					
4. ASCVD 10 year risk[b]	−.15	.87***	.89***				
5. Depressive symptoms[b]	−.04	−.10	−.05	−.04			
6. Positive affect[b]	.05	.15	.12	.08	−.57***		
7. Loneliness[b]	−.03	.09	.06	.16	.62***	−.53***	
8. Positive expressive skill[b]	.08	−.21[t]	−.35***	−.28*	.01	.03	−.03

*** $p < .001$; ** $p < .01$; * $p < .05$; [t] $p < .10$

[a] Spearmans correlation coefficients

[b] Pearsons correlation coefficients

degree of effort when producing expressions of target emotions (mean = 5.8, SD = 0.96). Although not included in the present analysis due to a relatively small sample size, all results are the same when the degree of effort is covaried.

Analytic approach

Univariate correlations were run to test associations between study variables. Following this, linear regressions were run on each of the three CVD risk scores. In each case, PES scores were entered in Step 1, followed by potential confounds; sex, PA, depressive symptoms, and loneliness in Step 2. Finally, the skill by sex interaction term was entered in Step 3. To compute interaction terms, PES scores were z-standardized and multiplied by the dichotomous sex scores (men = 0, women = 1). Where appropriate, simple slopes analysis was used to deconstruct interactions.

Results

Correlations

Univariate correlations between study variables revealed that greater PES was associated with lower NZ 5-year and ASCVD 10-year risk scores, and was marginally associated with lower Framingham 10-year risk scores. As would be expected, all three risk scores were positively correlated with one another. PA and depressive symptoms were negatively correlated, while loneliness was positively correlated with depression and negatively correlated with PA (see Table 2).

NZ 5-year projected CVD risk

Entering PES in the first step produced a significant model, $F (1, 80) = 11.17$, $p = .001$, explaining 12% variance in risk scores. As expected, PES predicted lower CVD risk scores ($\beta = −.35$, $p = .001$). The addition of covariates; sex, PA, depressive symptoms, and loneliness in Step 2 also produced a significant model, $F (5, 76) = 3.75$, $p = .004$, explaining a further 8% variance in risk scores, although the F-change was not significant, $F\varDelta (4, 76) = 1.78$, $p = .14$. PES continued to predict lower projected risk ($\beta = −.33$, $p = .002$), and being male was associated with marginally higher projected risk ($\beta = −.20$, $p = .064$). The inclusion of the sex-by-skill interaction term in the final step again produced a significant model, $F (5, 71) = 4.92$, $p = .001$, explaining a further 8% variance in risk scores, $F\varDelta (6, 75) = 4.54$, $p = .010$. PES continued to predict lower CVD risk scores ($\beta = −.81$, $p < .001$), however, this main effect was moderated by an interaction with sex ($\beta = .55$, $p = .010$) (see Table 3). Simple slopes analysis showed that lower PES predicted higher CVD risk scores among men, $t (19) = −3.93$, $p < .001$, but not women $t (61) = −1.41$, $p = .16$ (see Fig. 1).

ASCVD 10-year projected risk

Entering PES in Step 1 produced a significant model, $F (1, 80) = 6.74$, $p = .011$, explaining 8% variance in risk scores. As expected, greater PES predicted lower CVD risk scores ($\beta = −.28$, $p = .011$). The addition of covariates; sex, PA, depressive symptoms, and loneliness in Step 2 also produced a significant model, $F (5, 76) = 3.16$, $p = .012$, explaining a further 10% variance in risk scores, although the change in F was marginal, $F\varDelta (4, 76) = 2.17$,

Table 3 Results showing the final step for 3 linear regressions, showing how positive expressive skill (PES) and a PES by sex interaction predict projected CVD risk parameters while controlling for trait positive affect, depressive symptoms and loneliness

	Framingham 10 year risk						New Zealand 5 year risk						ASCVD 10 year risk					
	B	SE	β	p	sr^2	95% CI	B	SE	β	p	sr^2	95% CI	B	SE	β	p	sr^2	95% CI
PES	−1.68	0.62	−0.59	.009	0.08	−2.92, −0.44	−0.75	0.19	−0.81	.000	0.15	−1.13, −0.37	−1.31	0.37	−0.74	.001	0.13	−2.05, −0.58
Sex	−0.10	0.71	−0.02	.885	0.00	−1.52, 1.32	−0.32	0.22	−0.15	.147	0.02	−0.75, 0.12	−0.44	0.42	−0.11	.298	0.01	−1.29, 0.40
Positive affect	0.88	0.82	0.15	.282	0.01	−0.74, 2.51	0.26	0.24	0.14	.294	0.01	−0.23, 0.76	0.41	0.48	0.11	.403	0.01	−0.56, 1.37
Depressive symptoms	−0.05	0.05	−0.14	.341	0.01	−0.16, 0.06	0.00	0.02	−0.03	.813	0.00	−0.04, 0.03	−0.03	0.03	−0.12	.391	0.01	−0.09, 0.04
Loneliness	0.08	0.04	0.27	.059	0.04	0.00, 0.16	0.02	0.01	0.17	.213	0.02	−0.01, 0.04	0.06	0.02	0.31	.024	0.05	0.01, 0.11
Sex-by-skill interaction	1.50	0.73	0.45	.044	0.05	0.04, 2.95	0.59	0.22	0.55	.010	0.07	0.15, 1.14	1.15	0.43	0.56	.010	0.07	0.29, 2.02

sr^2 squared part correlations

1 Men = 0, Women = 1

$p = .080$; PES continued to predict lower risk ($\beta = -.26$, $p = .017$), while loneliness predicted higher risk ($\beta = .35$, $p = .014$). The addition of the sex-by-skill interaction term in the final step again produced a significant model, $F (6, 75) = 4.02$, $p = .002$, explaining a further 7% variance in risk scores, $F\Delta (1, 75) = 7.05$, $p = .010$. Greater PES continued to predict lower CVD risk scores ($\beta = -.74$, $p = .001$), and loneliness predicted higher risk ($\beta = .31$, $p = .024$). However, the main effect of PES was moderated by an interaction with sex ($\beta = .56$, $p = .010$) (see Table 3). Simple slopes analysis showed that lower PES predicted higher CVD risk scores among men, $t (19) = -3.55$, $p = .001$, but not women $t (61) = -.78$, $p = .44$ (see Fig. 1).

Framingham 10-year projected CVD risk

Entering PES in the first step produced a marginal model, $F (1, 80) = 3.60$, $p = .061$, explaining 4% variance in risk scores. PES marginally predicted lower CVD risk scores ($\beta = -.20$, $p = .061$). The addition of covariates; sex, PA, depressive symptoms, and loneliness in Step 2 also produced a marginal model, $F (5, 76) = 2.05$, $p = .081$, explaining a further 8% variance in risk scores, although the change in F was not significant, $F\Delta (4, 76) = 1.64$, $p = .17$. PES continued to marginally predict lower risk ($\beta = -.20$, $p = .073$), and loneliness predicted higher risk ($\beta = .30$, $p = .039$). The addition of the sex-by-skill interaction term in the final step did produce a significant model, $F (6, 75) = 2.48$, $p = .030$, explaining a further 5% variance in risk scores, $F\Delta (1, 75) = 4.19$, $p = .044$. PES predicted lower CVD risk scores ($\beta = -.59$, $p = .009$), however, the effect of PES was moderated by a significant interaction with sex ($\beta = .46$, $p = .044$) (see Table 3). Simple slopes analysis showed that lower PES predicted higher CVD risk scores among men, $t (19) = -2.69$, $p = .009$, but not women $t (61) = -0.52$, $p = .61$ (see Fig. 1).

Discussion

Positive emotionality and the tendency to express positive emotion have been associated with lower CVD risk (Davidson et al., 2010; Howell et al., 2007; Pressman & Cohen, 2005). To this, the present report adds the possibility that the *ability* to express positive emotion also has ties to measures of cardiac risk. As expected, greater ability to express positive emotion was associated with lower cardiac risk scores on three metrics, even after controlling for PA, depressive symptoms, and loneliness. Additional analyses suggested that this effect was primarily evident among men. Below, we discuss these results more fully, consider possible interpretations, and offer directions for future study.

The finding that the *ability* to express positive emotion was associated with lower CVD risk scores is consistent with evidence that trait positive expressivity is associated with lower cardiac risk (Davidson et al., 2010) and smile intensity predicts longevity (Abel & Kruger, 2010). Interpretatively, the ability to *deliberately* express positive emotion may reflect differences in an underlying capacity to self-regulate, which in turn has links with better health outcomes (Kubzansky et al., 2011; Potijk et al., 2016). Additionally, positive expressive skill may correspond with lower risk via social mechanisms, increasing available support and co-operation (Owren & Bachorowski, 2001) and reducing risk associated with social isolation (Valtorta et al., 2016).

However, moderation analyses suggested that the links between expressive skill and risk scores were predominantly evident in men. Interpretatively, although there were no clear sex differences in skill scores, such metrics may be more closely associated with risk in men due to either lower skill and/or higher risk scores in this group. Alternatively, positive expressive skill may serve a protective function that is more salient among men, by offsetting a typically less facilitative style of emotional signaling.
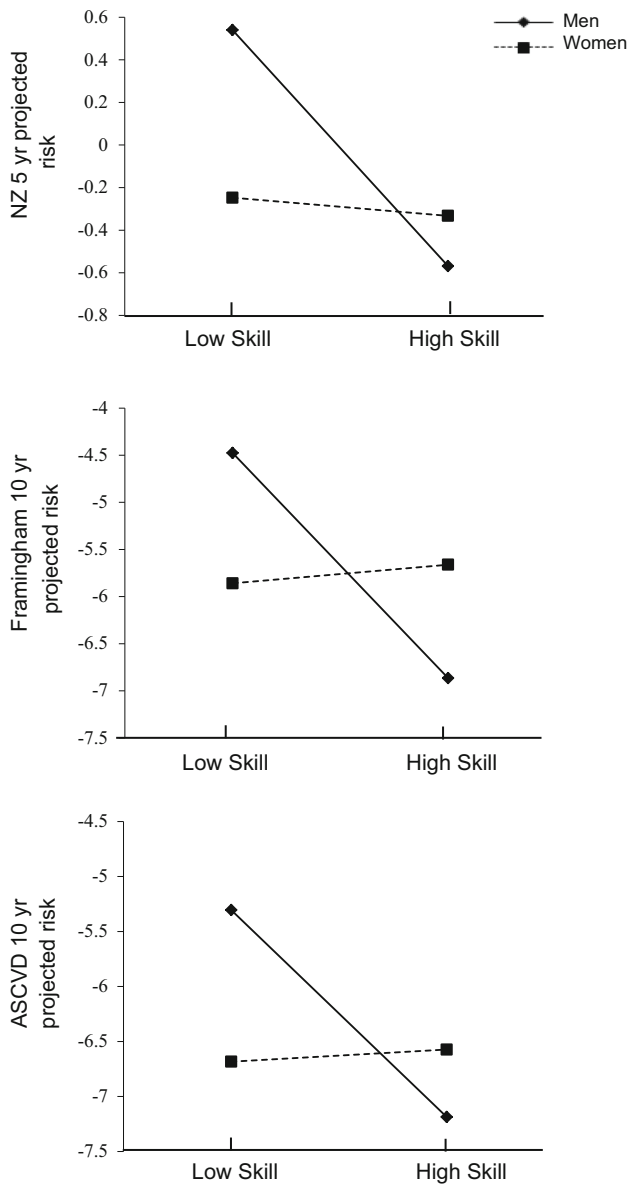
Fig. 1 Simple slopes showing the interactions between skill in expressing positive emotions and sex in predicting three measures of projected cardiovascular disease risk

Compared to women, men are more likely to express emotions that increase social distance (Hall et al., 2000), and respond to stressors with egocentricity and a 'fight or flight' response, potentially increasing CVD risk via allostatic load and social factors (Tomova et al., 2014; Valtorta et al., 2016). Conversely, positive expressions signal a willingness to interact and co-operate (Owren & Bachorowski, 2001), and the *ability* to deliberately signal positive emotion (regardless of felt emotion), may buffer CVD risk by improving social support, facilitating conflict resolution, and speeding autonomic recovery (e.g. Kraft & Pressman, 2012). Evidence that the links between psychosocial fac-

tors and disease risk are more apparent among men than women (Yang et al., 2013), may imply that the *cost* of expressive skill deficits might be higher for men.

Limitations and future directions

The present data have several limitations. Findings in a predominantly white sample cannot be generalized to other groups. Likewise, participants self-selected into the study, and CVD risk factors were relatively low. Selection biases (particularly among men) may be strong for a study titled 'Emotions and Health', and the present sample may not be representative of the broader population. Men were under-represented in the present sample, and, marginal effects in some models may indicate that the study was underpowered. Further studies in larger, more representative, gender-balanced samples are needed to confirm these findings.

Additionally, despite controlling for several established confounds, the cross-sectional design means that third variable confounds are nonetheless possible and the ability to express positive emotion may be confounded with the ability to generate positive affect. Additionally, the direction of the relationship remains unclear. It is, for example, possible that men in poorer health are less able to signal positive emotions. Relatedly, skill deficits might reflect differences in motivation, attention, or system fatigue, although controlling for reported effort did not influence the present findings.

Further, it is important to note that risk metrics cannot be generalized to actual cardiac events, and future work is needed to test whether expressive skills predict cardiac morbidity or mortality. Rather, risk metrics reflect a combination of biological, demographic, and behavioral risk factors, and a single risk factor (or group of factors) may be responsible for the observed link between expressive skill and risk scores. Although correlations between skill scores and individual risk metrics were not significant, and did not indicate that any single metric (or group of metrics) was responsible, future studies identifying the specific risk factors that are most strongly associated with expressive skills would help to identify the mechanisms by which expressive skills are associated with CVD risk scores. This noted, risk scores are only reliable predictors of outcome among middle aged and older samples (D'Agostino et al., 2008; Dawber et al., 1951; Lloyd-Jones et al., 2004) and studies in younger samples and student groups are not well suited to the examination of links between expressive skills and cardiac risk algorithms.

Finally, the ability to signal negative emotions may also be associated with better health outcomes, however several issues prevented exploration of this possibility in the current report. First, in contrast to the positive expressive skill metrics, the negative skill scores were poorly distributed

and ill-suited to parametric testing. This may indicate that signaling specific negative emotions is more challenging than showing positivity (at least in this measurement context). Second, participants often tilted their heads of covered their faces while expressing negative emotions, meaning that the FaceReader ^{TM} software was unable to generate valid expressivity estimates for negative expressions for an additional 20 participants (reducing the sample size from 82 to 62). Third, although combining negative skills scores into a single negative affect skill metric did produce a normally distributed aggregate that was associated with lower CVD risk scores, the alpha coefficient was low ($\alpha = .15$), suggesting that combining these variables is not empirically warranted. Thus, although the present findings are limited to positive expressive skill, it seems likely that skill in expressing negative emotions may also predict health outcomes, and future studies testing this possibility are needed.

Despite limitations, this report provides early empirical evidence that an objective test of the ability to signal positive emotion predicts projected cardiac risk. It extends prior findings linking both trait PA and positive expressivity with health outcomes, and implies that the *ability* to signal positive emotion may underpin some of these links. Given that the biological, behavioral, and demographic risk factors measured here are relevant to other chronic conditions, notably diabetes (Singh et al., 2013; Wulsin et al., 2015), the observed links between skills and CVD risk scores may extend to other health outcomes.

Compliance with ethical standards

Conflict of interest Natalie L. Tuck, Kathryn S. Adams, Sarah D. Pressman, and Nathan S. Consedine declares that they do not have any conflict of interest.

Human and animal rights and Informed consent The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008. Informed consent was obtained from all patients for being included in the study.

References

Abel, E. L., & Kruger, M. L. (2010). Smile intensity in photographs predicts longevity. *Psychological Science, 21,* 542–544. doi:10.1177/0956797610363775

Appleton, A. A., & Kubzansky, L. D. (Eds.). (2014). *Emotion regulation and cardiovascular disease risk* (2nd ed.). New York: The Guilford Press.

Appleton, A. A., Loucks, E. B., Buka, S. L., Rimm, E., & Kubzansky, L. D. (2013). Childhood emotional functioning and the developmental origins of cardiovascular disease risk. *Journal of Epidemiology and Community Health, 67,* 405–411. doi:10.1136/jech-2012-201008

Boyle, G. J., Helmes, E., Matthews, G., & Izard, C. E. (2015). Measures of affect dimensions. In *Measures of personality and social psychological constructs* (pp. 190–224).

Chida, Y., & Steptoe, A. (2008). Positive psychological well-being and mortality: A quantitative review of prospective observational studies. *Psychosomatic Medicine, 70,* 741–756.

Cohen, A. S., Morrison, S. C., & Callaway, D. A. (2013). Computerized facial analysis for understanding constricted/blunted affect: Initial feasibility, reliability, and validity data. *Schizophrenia Research, 148,* 111–116. doi:10.1016/j.schres.2013.05.003

Consedine, N. S., Magai, C., & Bonanno, G. A. (2002). Moderators of the emotion inhibition-health relationship: A review and research agenda. *Review of General Psychology, 6,* 204–228.

D'Agostino, R. B., Vasan, R. S., Pencina, M. J., Wolf, P. A., Cobain, M., Massaro, J. M., et al. (2008). General cardiovascular risk profile for use in primary care the Framingham Heart Study. *Circulation, 117,* 743–753.

Davidson, K. W., Mostofsky, E., & Whang, W. (2010). Don't worry, be happy: Positive affect and reduced 10-year incident coronary heart disease: The Canadian Nova Scotia Health Survey. *European Heart Journal*. doi:10.1093/eurheartj/ehp603

Dawber, T. R., Meadors, G. F., & Moore, F. E., Jr. (1951). Epidemiological approaches to heart disease: The Framingham Study. *American Journal of Public Health and the Nations Health, 41,* 279–286.

Eichler, K., Puhan, M. A., Steurer, J., & Bachmann, L. M. (2007). Prediction of first coronary events with the Framingham score: A systematic review. *American Heart Journal, 153,* e728. doi:10.1016/j.ahj.2007.02.027

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G* Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41,* 1149–1160.

Fredrickson, B. L. (2013). Positive emotions broaden and build. *Advances in Experimental Social Psychology, 47,* 1–53.

Goff, D., Lloyd-Jones, D., Bennett, G., Coady, G., D'Agostino, R., & Gibbons, R. (2013). On the assessment of cardiovascular risk: A report of the American College of Cardiology/American Heart Association task force on practice guidelines. *Circulation, 29,* S49–S73.

Hall, J. A., Carter, J. D., & Horgan, T. G. (2000). Gender differences in nonverbal communication of emotion. In A. H. Fischer (Ed.), *Gender and emotion: Social psychological perspectives* (pp. 97–117). Paris: Cambridge University Press.

Harker, L., & Keltner, D. (2001). Expressions of positive emotion in women's college yearbook pictures and their relationship to personality and life outcomes across adulthood. *Journal of Personality and Social Psychology, 80,* 112. doi:10.1037/0022-3514.80.1.112

Hayashi, K., Kawachi, I., Ohira, T., Kondo, K., Shirai, K., & Kondo, N. (2016). Laughter is the best medicine? A cross-sectional study of cardiovascular disease among older Japanese adults. *Journal of Epidemiology, 26,* 546–552.

Haynes, S., Feinleib, M., & Kannel, W. B. (1980). The relationship of psychosocial factors to coronary heart disease in the Framingham Study. III. Eight-year incidence of coronary heart disease. *American Journal of Epidemiology, 111,* 37–58.

Howell, R. T., Kern, M. L., & Lyubomirsky, S. (2007). Health benefits: Meta-analytically determining the impact of well-being

on objective health outcomes. *Health Psychology Review, 1,* 83–136.

Izard, C. E., Libero, D. Z., Putnam, P., & Haynes, O. M. (1993). Stability of emotion experiences and their relations to traits of personality. *Journal of Personality and Social Psychology, 64,* 847.

Jackson, R. (2000). Updated New Zealand cardiovascular disease risk-benefit prediction guide. *BMJ, 320,* 709–710.

Jones, A. F., Walker, J., Jewkes, C., Game, F. L., Bartlett, W. A., Marshall, T., et al. (2001). Comparative accuracy of cardiovascular risk prediction methods in primary care patients. *Heart, 85,* 37–43. doi:10.1136/heart.85.1.37

Kraft, T. L., & Pressman, S. D. (2012). Grin and bear it the influence of manipulated facial expression on the stress response. *Psychological Science, 23,* 1372–1378. doi:10.1177/0956797612445312

Kubzansky, L. D., Park, N., Peterson, C., Vokonas, P., & Sparrow, D. (2011). Healthy psychological functioning and incident coronary heart disease: The importance of self-regulation. *Archives of General Psychiatry, 68,* 400–408. doi:10.1001/archgenpsychiatry.2011.23

Lewinski, P. (2015). Automated facial coding software outperforms people in recognizing neutral faces as neutral from standardized datasets. *Frontiers in Psychology, 6,* 1386. doi:10.3389/fpsyg.2015.01386

Lloyd-Jones, D. M., Wilson, P. W., Larson, M. G., Beiser, A., Leip, E. P., D'Agostino, R. B., et al. (2004). Framingham risk score and prediction of lifetime risk for coronary heart disease. *The American Journal of Cardiology, 94,* 20–24.

Loijens, L., Krips, O., Kuilenburg, H. V., Uyl, M. D., Ivan, Paul, Theuws, H., et al. (2014). *Reference manual FaceReader^{TM} version 6.* The Netherlands: Wageningen.

Orme, J. G., Reis, J., & Herz, E. J. (1986). Factorial and discriminant validity of the center for epidemiological studies depression (CES-D) scale. *Journal of Clinical Psychology, 42,* 28–33.

Owren, M. J., & Bachorowski, J.-A. (2001). The evolution of emotional experience: A "selfish-gene" account of smiling and laughter in early hominids and humans. In T. J. Mayne & G. A. Bonanno (Eds.), *Emotions: Currrent issues and future directions* (pp. 152–191). New York: Guilford Press.

Potijk, M. R., Janszky, I., Reijneveld, S. A., & Falkstedt, D. (2016). Risk of coronary heart disease in men with poor emotional control: A prospective study. *Psychosomatic Medicine, 78,* 60–67.

Pressman, S. D., & Cohen, S. (2005). Does positive affect influence health? *Psychological Bulletin, 131,* 925–971. doi:10.1037/0033-2909.131.6.925

Radloff, L. S. (1977). The CES-D scale: A self-report depression scale for research in the general population. *Applied Psychological Measurement, 1,* 385–401. doi:10.1177/014662167700100306

Russell, D. W. (1996). UCLA Loneliness Scale (Version 3): Reliability, validity, and factor structure. *Journal of Personality Assessment, 66,* 20–40.

Singh, G. M., Danaei, G., Farzadfar, F., Stevens, G. A., Woodward, M., Wormser, D., et al. (2013). The age-specific quantitative effects of metabolic risk factors on cardiovascular diseases and diabetes: A pooled analysis. *PLoS ONE, 8,* e65174.

Soussignan, R. (2002). Duchenne smile, emotional experience, and autonomic reactivity: A test of the facial feedback hypothesis. *Emotion, 2,* 52.

Tomova, L., von Dawans, B., Heinrichs, M., Silani, G., & Lamm, C. (2014). Is stress affecting our ability to tune into others? Evidence for gender differences in the effects of stress on self-other distinction. *Psychoneuroendocrinology, 43,* 95–104. doi:10.1016/j.psyneuen.2014.02.006

Tuck, N. L., Grant, R. I., Jackson, A. S., Brooks, A., & Consedine, N. S. (2016a). Beyond self-report: Performance measures of emotional competencies predict symptoms of depression and anxiety, physical symptoms, self-rated health and immunoregulatory molecules. *Annals of Behavioral Medicine.* doi:10.1007/s12160-016-9809-5

Tuck, N. L., Grant, R. I., Sollers, J. J., III, Booth, R. J., & Consedine, N. S. (2016b). Higher resting heart rate variability predicts skill in expressing some emotions. *Psychophysiology.* doi:10.1111/psyp.12755

Valtorta, N. K., Kanaan, M., Gilbody, S., Ronzi, S., & Hanratty, B. (2016). Loneliness and social isolation as risk factors for coronary heart disease and stroke: Systematic review and meta-analysis of longitudinal observational studies. *Heart.* doi:10.1136/heartjnl-2015-308790

Wood, D., Wray, R., Poulter, N., Williams, B., Kirby, M., Patel, V., et al. (2005). JBS 2: Joint British Societies' guidelines on prevention of cardiovascular disease in clinical practice. *Heart, 91,* v1–v7. doi:10.1136/hrt.2005.079988

Wulsin, L. R., Horn, P. S., Perry, J. L., Massaro, J. M., & D'agostino, R. B. (2015). Autonomic imbalance as a predictor of metabolic risks, cardiovascular disease, diabetes, and mortality. *The Journal of Clinical Endocrinology & Metabolism, 100,* 2443–2448.

Yang, Y. C., McClintock, M. K., Kozloski, M., & Li, T. (2013). Social isolation and adult mortality: The role of chronic inflammation and sex differences. *Journal of Health and Social Behavior.* doi:10.1177/0022146513485244