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The Relationship Between Emodiversity and Health Is Robust, Replicable, and Theoretically Grounded

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In 2014 in the *Journal of Experimental Psychology: General*, we reported two studies demonstrating that the diversity of emotions that people experience—as measured by the Shannon-Wiener entropy index—was an independent predictor of mental and physical health, over and above the effect of mean levels of emotion. Brown and Coyne questioned both our use of Shannon's entropy and our analytic approach. We thank Brown and Coyne for their interest in our research; however, both their theoretical and empirical critiques do not undermine the central theoretical tenets and empirical findings of our research. We present an in-depth examination that reveals that our findings are statistically robust, replicable, and reflect a theoretically grounded phenomenon with real-world implications.

Keywords: emotional complexity, emodiversity, health, replication, robustness

In 2014, we (Quoidbach et al., 2014) reported two studies in the *Journal of Experimental Psychology: General* in which we found that the diversity of emotion that people experience was related to mental and physical health. Building on the idea that emotions such as stress, anger, or sadness might be particularly detrimental when they dominate mental life and that specific, differentiated emotional states have more adaptive value than do global affective states (e.g., Barrett & Gross, 2001; Kehner, Locke, & Aurain, 1993; Schwarz, 1990), we adapted the Shannon biodiversity index (Shannon, 1948) to quantify *emodiversity*: the richness (how many specific emotions are experienced) and evenness (the extent to which specific emotions are experienced in the same proportion) in the human emotional ecosystem:

$$\text{Emodiversity} = -1 \times \sum_{i=1}^{s} (P_i \times \ln P_i) \tag{1}$$

where s is the total number of emotions experienced (richness) and p_i is the proportion of s made up of the ith emotions. We entered mean levels of emotion, emodiversity, and their interactions into a series of regressions and found that emodiversity of both positive and negative emotion independently predicted lower depression and better objective physical health beyond mean levels of emotion. While we were careful to temper our claims regarding the small effect sizes, potential causal directions, and underlying pathways by which emodiversity relates to health outcomes, we argued that emodiversity was a previously unidentified metric that, in conjunction with traditional average levels of emotion, could be used to assess meaningful differences in people's emotional experience.

In their commentary "Emodiversity: Robust predictor of outcomes or statistical artifact?" Brown and Coyne (2017) argued that our use of Shannon's entropy to measure the diversity of emotion is "highly questionable" and that our key results are likely to be due to "a set of computational and statistical artifacts" (p. ●●●). AQ: 5 The core of Brown and Coyne's theoretical critique is that the use of a diversity index such as Shannon's is not applicable to the typical emotion scales used in psychology because, unlike count observations a biologist could make about the diversity of species in an ecosystem, these measures are limited both in terms of the number of emotion items (not all emotions can be measured) and the range of the response scale (e.g., 1 to 5). The core of Brown and Coyne's empirical critique is that we did not conduct hierarchical regression, which they argued highlights that some of the

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effects in our Study 1 are small, and that there are signs of statistical suppression in Study 2.

We thank Brown and Coyne (2017) for their interest in our work, but disagree on both points. Below, we demonstrate that both the theoretical and empirical critiques presented by Brown and Coyne are largely unfounded and do not undermine the central conclusions of the original published article. We further provide the results of a recent large-scale replication of the relationship between emodiversity and objective health, which is fully consistent with our original findings, and cite other recent research by independent scholars that replicates our core results.

Theoretical Critique

Biologists typically use Shannon's entropy index to quantify, in a single metric, the richness and evenness of an ecosystem that is, the number of distinct species and their relative abundance. Such metric is important as it allows to measure diversity, which combined to the total number of living organisms (i.e., biomass), help characterize the health of our ecosystems. Similarly, we used Shannon's entropy index to quantify, within a single metric, the richness (how many specific emotions are experienced) and evenness (the extent to which specific emotions are experienced in the same proportion) in the human emotional ecosystem. We proposed that combining such diversity index with the typical measure of the total number of emotions may provide a more detailed picture of people's emotional lives. Brown and Coyne (2017) challenged our application of Shannon's entropy because they believe the transposition of the concepts of both richness and evenness to the domain of emotions are subject to series of limitations.

Before responding to each of these points in detail below, we note that Shannon's diversity index and similar measures of entropy have been widely used in previous psychological research; in short, we are far from the first scholars to use such measures to shed novel, useful insight into psychological phenomena. To name just a few, such indices have been used to quantify stressor diversity (Koffer, Ram, Conroy, Pincus, & Almeida, 2016), social diversity (Vaquero & Cebrian, 2013), activity diversity (Lee et al., 2016), ethnic diversity within a community (Budescu & Budescu, 2012), diversity in work teams (Schippers, Den Hartog, Koopman, & Wienk, 2003), social diversity of an individual's interaction partners (Ram, Conroy, Pincus, Hyde, & Molloy, 2012), behavioral diversity of mother–child dyads (Lichtwarck-Aschoff, Hasselman, Cox, Pepler, & Granic, 2012), cognitive diversity within an individual (Hirsh, Mar, & Peterson, 2012), and diversity in children's behavior (Helm, Ram, Cole, & Chow, 2016). Although Shannon's diversity index originated in a different field, it is now a well-established method of assessing diversity in social science research. In a sense, we (simply) applied the construct to the domain of emotion. In fact, since the publication of our original article (Quoidbach et al., 2014), several published research articles have used the emodiversity metric to uncover important individual differences (e.g., Benson, Ram, Almeida, Zautra, & Ong, 2017; Grossmann, Gerlach, & Denissen, 2016; Ong, Benson, Zautra, & Ram, 2017) and cross-cultural differences (Grossmann, Huynh, & Ellsworth, 2016) in emotional complexity. Brown and Coyne (2017) raised two specific conceptual issues with respect to the richness and evenness of emotions, the two central constructs which constitute the emodiversity index.

Richness

Brown and Coyne (2017) believed that our emodiversity index—which we derive using nine- and 18-item (Study 1) and 10- and 20-item (Study 2) emotion scales—does not capture the richness of one's emotion because doing so would require measuring the "greatest possible number of emotions" (p. ●●●). The gist of their argument derives from an analogy: sending a field biologist out to report the number of (only) rabbits, mice, rats, voles, and beavers, while ignoring foxes because there was no corresponding space on the form, might lead to suboptimal assessment. However, even in biology, Shannon's index is used with the knowledge that the set of species counted is incomplete: indeed, an estimated 86% of existing species on Earth still await to be discovered, but this fact has not prevented biologists from monitoring and comparing biodiversity levels across the globe (Mora, Tittensor, Adl, Simpson, & Worm, 2011). And even more importantly for our account, recent independent follow-up research—which replicates the link we observe between emodiversity and health—demonstrates that the emodiversity index is robust to the number of emotion items included in the scale (Benson et al., 2017); the authors show that the rank ordering of emodiversity scores derived from 32-item and 10-item emotion scales are very high ($r = .90$). Thus, Benson et al. (2017) suggested that in fact the mere number of emotions included in the index is not a critical factor in determining the validity of the emodiversity measure.

More generally, we would note that requiring researchers to include a fully comprehensive set of behaviors, attitudes, or emotions in an assessment of diversity is in practice impossible. While there are thousands of words that can be used to describe the subtle nuances of human emotional experience—for example, the word *waldeinsamkeit*, from the German meaning "the feeling of being alone in the woods"—we suggest that an index lacking this specific emotion, but containing a sufficient number of commonly experienced emotions, likely still offers psychological insight. As a result, we believe that our decision to use a limited set of emotion items is appropriate—and in keeping with the more than 25,000 articles (per Google Scholar) that have cited the most commonly used index, the 10-item Positive and Negative Affect Schedule (Watson, Clark, & Tellegen, 1988).

Evenness

Brown and Coyne (2017) noted that the 5-point Likert scales that we used in our studies (Quoidbach et al., 2014) are limited in range and, as a result, the emodiversity scores we derive from our emotion scales are likely to be more influenced by the number of emotions people report experiencing (i.e., richness) than by the evenness of the distribution of items. We are thankful for this insightful comment with which we fully agree. In fact, our own follow-up ongoing work on emodiversity measurement suggests that switching to a 21-point response format while continuing to use standard emotion scale gives roughly the same weight to richness and evenness in the total emodiversity score (see Figure 1). We reached this conclusion by simulating 10,000 random F1 emotion ratings on 5-, 10-, 20-, 30-, 40-, 50-, 60-, 70-, 80-, 90-, and 100-point scales. With small-range rating scales, the emodiversity score is mainly correlated with the richness of emotions (how many emotions were experienced at least a little; *white dots*); with

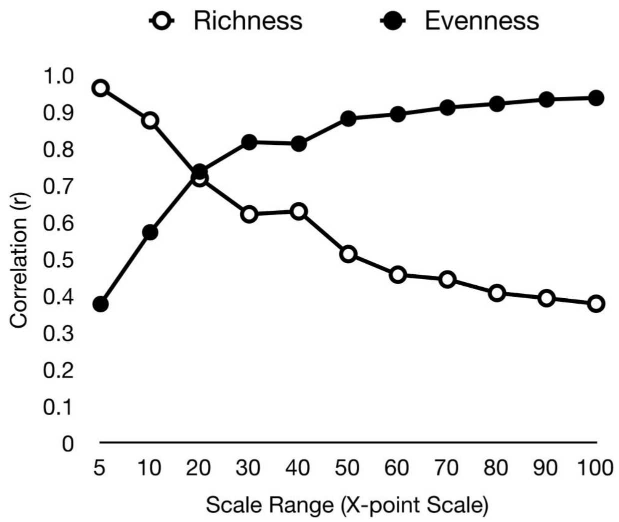

Figure 1. Correlation between emodiversity and its two subcomponents (richness and evenness) for different types of response scale.

large-range rating scales, the score is mainly correlated with the evenness of the emotion distribution (*black dots*).

We note, however, that while these technical considerations are important for researchers interested in computing a diversity score that would weigh equally the richness and evenness components of people's emotion reports, we did not have specific hypotheses nor make any claims about the respective roles of richness and evenness. Our article (Quoidbach et al., 2014) was the first to suggest that the general diversity of emotions that people report—taking into account *both* evenness and richness—has predictive value over and above their average level of emotions; there is clearly room for future research to further refine these findings, exploring specific roles for the two components of the emodiversity index.

At its core, Brown and Coyne (2017)'s concern about the number of items (richness) and the range of the Likert scales (evenness) we used is that our emodiversity scores might be "unlikely to provide any meaningful amount of variance, independent of the underlying emotion measure, to be explained empirically" (p. ●●●). To support this view, Brown and Coyne reported that the ratio between the lowest and highest possible emodiversity values in Study 1 is very small, mentioning 1.1:1. They argued—without providing empirical evidence—that individual differences on such small range are not meaningful. We find this claim puzzling for two reasons. First, meaningful variance in a population is not a matter of ratio. Small numerical differences can reflect huge differences in real life. To take only one example, the ratio between life-threatening hyperpyrexia (≈41°C) and normal body temperature (≈37°C) in adults is only 1.1:1. Second, the ratios Brown and Coyne computed are incorrect. Brown and Coyne stated that the ratio between the lowest and highest theoretically possible emodiversity values is 1.1:1. In fact, in our data, these ratios are 4.4:1 for Study 1 and 5.3:1 for Study 2—even if we exclude people who have an emodiversity score of 0 (see Figure 2). F2

While Brown and Coyne (2017)'s simulations did not demonstrate that there is insufficient variance in emodiversity scores, they did demonstrate that using a 5-point Likert scale to measure emotion results in little variation between two hypothetical individuals with the same level of richness (i.e., who experience the same number of emotions). In other words, they showed, as previously mentioned, that in our studies, the evenness component of emodiversity plays a relatively weak role compared to the richness component in people's emodiversity scores. Critically, however, recent research demonstrates that the evenness component of diversity also predicts better health (Benson et al., 2017; Ong et al., 2017); taken together, our results, Benson et al. (2017), and Ong et al. (2017) suggest that both components play a role; again, we agree that further research is needed to unpack their relative roles.

Validity and Data Quality

Brown and Coyne (2017) noted that the highest and lowest emodiversity scores could occur if participants are not responding correctly to the scales: If participants selected the same response for all emotion items (e.g., "sometimes") because, for example, they aren't paying attention, this would result in maximal emodiversity scores; if participants selected the response "never" for all emotion items, this would result in minimal emodiversity scores. We note that these concerns apply to countless studies that employ Likert scales, but nonetheless assessed whether unusual responding was a concern in our studies by checking the percentage of

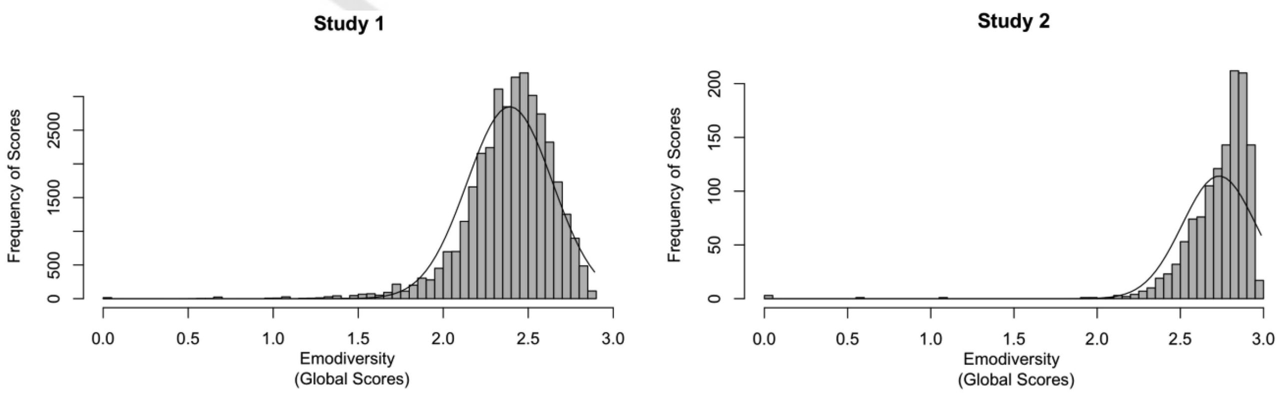

Figure 2. Distribution of emodiversity scores in Study 1 and Study 2 (Quoidbach et al., 2014).

participants who reported experiencing all emotions “never,” or all to the same degree. In Study 1, 0.8% of participants responded “never” and 0.9% reported experiencing all items to the same degree for positive emotion, whereas 3.4% responded “never” and 0.2% reported experiencing all items to the same degree for negative emotion. In Study 2, 0.1% of participants responded “never” and 1.1% reported experiencing all items to the same degree for positive emotion, whereas 0.3% responded “never” and 2.0% reported experiencing all items to the same degree for negative emotion. Thus, such patterns of responses were quite rare. Moreover, all regression coefficients remained virtually identical when these participants were excluded from our analyses (see Table 1).

Wording Choices

We stated that emodiversity reflects “the variety and relative abundance of the emotions people experience” (Quoidbach et al., 2014, p. ●●●). Brown and Coyne (2017) argue that we do not measure abundance of emotions because a person experiencing 10 emotions “sometimes” receives the same emodiversity score as a person experiencing 10 emotions “very often.” To be clear, by abundance we mean “the quantity or amount of something present in a particular area, volume, or sample” (Quoidbach et al., 2014, p. ●●●), consistent with the characterization of relative abundance in previous research using Shannon’s index (e.g., Adekunle, 2006; Nagendra, 2002; Tramer, 1969). Emodiversity is not a measure of total frequency or intensity but a measure of the pattern or spread of people’s emotions—a common distinction in research on emotional complexity (see, e.g., Gruber, Kogan, Quoidbach, & Mauss, 2013; Grühn, Lumley, Diehl, & Labouvie-Vief, 2013; Pond et al., 2012). Therefore, it is true that one person experiencing 10 emotions “sometimes” and another person experiencing 10 emotions “very often” can obtain the same emodiversity score. In fact, this is exactly the key contribution of the emodiversity metric: It provides an index of the complexity of people’s emotional life that complements the mean level of emotions. This is precisely why we believe it is critical to examine emodiversity, the mean level of emotion, and their interaction simultaneously, as we did throughout our original article (Quoidbach et al., 2014).

Table 1
Partial Correlation Between Emodiversity and Health Outcomes, Controlling for Mean Level of Emotions and Emodiversity by Mean-Level Interactions

Study	Original paper[a]	Reanalysis without potential outliers
Study 1 (Depression)		
Positive emodiversity	.36***	.34***
Negative emodiversity	.20***	.18***
Global emodiversity	.07***	.07***
Study 2 (Doctor’s visits)		
Positive emodiversity	–.12***	–.12***
Negative emodiversity	–.07*	–.08**
Global emodiversity	–.10**	–.11***
Study 2 (Days spent hospitalized)		
Positive emodiversity	–.05	–.05
Negative emodiversity	–.06*	–.06*
Global emodiversity	–.10**	–.10**
Study 2 (Mean defined daily dose)		
Positive emodiversity	–.10***	–.09**
Negative emodiversity	–.13***	–.13***
Global emodiversity	–.12***	–.13***

[a] Quoidbach et al. (2014).
* $p < .05$. ** $p < .01$. *** $p < .001$.

Empirical Critique

In two studies, we entered mean levels of emotion, the entropy of the distribution that we called *emodiversity*, and their interactions into a series of regressions predicting mental and physical health. We found that emodiversity independently predicted lower depression and better physical health beyond mean levels of emotion. Brown and Coyne (2017) reanalyzed our data and found the same results. We interpret these results as an indication that frequently experiencing a diverse range of emotions is beneficial—a finding in line with dozens of studies examining other beneficial aspects of emotional complexity and the adaptive role of emotion (see Grossmann & Ellsworth, 2017; Grossmann, Huynh, et al., 2016; and Lindquist & Barrett, 2008, for reviews).

In contrast, Brown and Coyne (2017) suggested that our key results “may reduce to little more than a set of computational and statistical artifacts” (p. ●●●) because our effect sizes are small, one regression (out of three) has high variance inflation factors (VIFs), and there are signs of statistical suppression. We address each of these concerns below.

Effect Size

In our original article (Quoidbach et al., 2014), we stated that the effect sizes of our emodiversity measures were small compared to mean positive and negative affect and accounted for about 1% of the variance in depression (see p. 2061). While Brown and Coyne’s (2017) reanalysis of Study 1 was consistent with that conclusion for positive emodiversity, it highlighted that the interaction term is the only source of additional variance explained in the regression for negative emotion and negative emodiversity. These results suggested that negative emodiversity may not have, by itself, a protective effect on depression. However, when applied to Study 2’s objective health data, Brown and Coyne’s analyses—focusing on changes in R-squared—interestingly showed that negative emodiversity, in fact, does explain an additional 1.1% of unique variance in number of visits to the doctor, 1.2% of the variance in number of days spent in the hospital, and 1.6% of the variance in medication consumption and that these effects are of similar magnitude to mean levels of negative emotion (1.3%, 2.0%, and 0.6%, respectively). Across the two studies, then, analyses suggested that both positive and negative emodiversity predict health outcomes.

More generally, we note that while the variance in health explained by emodiversity is statistically modest, many well-established effects in psychology and health are small despite being of crucial practical importance. We are pleased that psychology is moving away from sole reliance p values to focus also on effect sizes—which is why we reported them in the first place—but this does not suggest that it is wise to dismiss findings solely because the statistical effect sizes are small (see Prentice & Miller, 1992). Consider the effect of aspirin consumption and heart attack risk

(0.1% of the variance); if physicians had dismissed the 0.1% of variance effect size in the aspirin and heart attack clinical trials, an additional 3.4% of their patients at risk would have suffered from a heart attack (Rosenthal, Rosnow, & Rubin, 2000). Similarly, the effect size of emodiversity in our original research (Quoidbach et al., 2014) is far from trivial. While we reported standardized effect sizes and regression coefficients, an examination of the raw regression coefficients indicates that an increase of one standard deviation in emodiversity equates to annual savings of 993.22 euros per person, per year, for the Belgian government.

Variance Inflation Factors and Multicollinearity

Brown and Coyne (2017) noted that in one of the three regressions reported in Study 1, the VIFs of the predictors become large when the interaction term of the average level of emotion and emodiversity is entered into the regression and claimed—without providing evidence—that multicollinearity might play a role in explaining our results. While noting that the other two regression analyses for negative emodiversity and global emodiversity do not yield particularly high VIFs, we examined whether multicollinearity might play a role in our analyses of positive emodiversity.

The most common problem that arises with multicollinearity is an increase in the standard errors of the regression coefficients, which means that the coefficients for some independent variables may be found not to be significantly different from 0 (see, e.g., Smith & Sasaki, 1979). In other words, by overinflating the standard errors, multicollinearity increases the risk of false negatives (i.e., some variables are found statistically insignificant when they should be significant). Therefore, in most cases, multicollinearity might have made it more difficult for us to find significant effects of emodiversity. In fact, removing the interaction term from the regression addresses the multicollinearity concern (as indicated by relatively normal VIFs); but importantly, the effect of positive emodiversity on depression remains significant (original data: $ß = -.36$, $t = 20.14$, $r_{\text{partial}} = -.11$, $p < .0001$; reanalysis: $ß = -.18$, $t = 27.52$, $r_{\text{partial}} = -.15$, $p < .0001$; Quoidbach et al., 2014). Given the logic above, these results argue against Brown and Coyne's (2017) alternative explanation that the effect of positive emodiversity is a statistical artifact created by variance inflation: The result still holds when variance inflation is no longer an issue.

Multicollinearity could have resulted in another issue: when an interaction term is composed of correlated variables, linearity and additivity become confounded. The result of this confounding is that an interaction term in the multiple regression may be statistically significant only because of its overlap with unmodeled nonlinear terms (Cortina, 1993). In other words, it is theoretically possible that emodiversity, rather than being an independent construct, captures the nonlinearity of the relationship between mean positive emotion and depression. To test this possibility, we entered both the linear and quadratic terms for the mean level of positive emotion, positive emodiversity, the Linear Mean Level $\times$ Diversity, and the Quadratic Mean Level $\times$ Diversity interactions into a regression predicting depression. Results indicate that positive emodiversity remained a significant predictor of mental health (original data: $ß = -.36$, $t = 20.14$, $r_{\text{partial}} = -.11$, $p < .0001$; reanalysis: $ß = -.34$, $t = 16.95$, $r_{\text{partial}} = -.09$, $p < .0001$; Quoidbach et al., 2014). Thus, an unmodeled potential nonlinear association between mean positive emotion and depression does not appear to account for the relationship between positive emodiversity and depression.

Finally, multicollinearity can lead to the problem of "bouncing betas," whereby small fluctuations of the sampling can cause large changes in the values and signs of the regression coefficients (Smith & Sasaki, 1979). To assess this possibility, we drew a thousand bootstrap resamples with replacement of sample sizes 1,000, 2,000 and 35,844 (the original sample size; Quoidbach et al., 2014) and computed the estimates of mean positive emotion, positive emodiversity and their interaction for each of the resamples. Figure 3 displays the distribution of the estimates in the F3 thousand resamples; we have added a vertical line at zero to indicate how many resamples gave an estimated value of the coefficient below zero because, based on our original results, we expect all the coefficients to be negative. The results are clear: it is extremely infrequent to obtain positive estimates of the parameters in a (random) subsample of our data, even when we dramatically reduce the size of the sample (e.g., 1,000 or 2,000 instead of the original 35,844). In addition, the distribution of the estimates looks like what one would expect: normal, with decreasing variance as the number of observations in the subsample increases, and always centered around values very close to the ordinary least squares estimates. Taken together with the other analyses above, AQ: 8 these results suggest that the relationship between positive emodiversity and depression is not spuriously created by multicollinearity.

Suppression Effects

Brown and Coyne (2017) compared the magnitude of the 18 zero-order correlations between emodiversity and health outcomes we reported in Study 2 with the 18 β coefficients of the respective regression models in which we controlled for mean level of emotion and the mean-level by emodiversity interactions. Brown and Coyne claimed that because these regression coefficients are bigger than their respective zero-order correlations, suppression effects must have occurred. Brown and Coyne further argued that these suppression effects make our results uninterpretable in the absence of a solid theoretical explanation. Following the recommendations of MacKinnon, Krull, and Lockwood (2000), we first tested whether, as Brown and Coyne (2017) claimed, suppression was present in all of our regressions models using Sobel tests. As shown in Table 2, there was no significant suppression effect for T2, AQ:9 the regressions involving positive emotion.

Negative emotion, however, did act as a significant suppressor. In other words, the beneficial effect of negative and global emodiversity on health both became stronger when mean negative emotion was entered in the regressions. According to Paulhus, Robins, Trzesniewski, and Tracy (2004), suppression effects are problematic in psychology (a) when one does not have a theory to support the reported relationship and (b) when such effects do not replicate in other samples.

Our theoretical account in our original article (Quoidbach et al., 2014) clearly noted that emodiversity may act as a buffer against the deleterious effect of negative emotion (see p. 2064). Critically, we base our theoretical account on decades of research revealing the importance of emotion complexity and differentiation (e.g., Bao & Lyubomirsky, 2013; Barrett & Gross, 2001; Barrett, Gross,

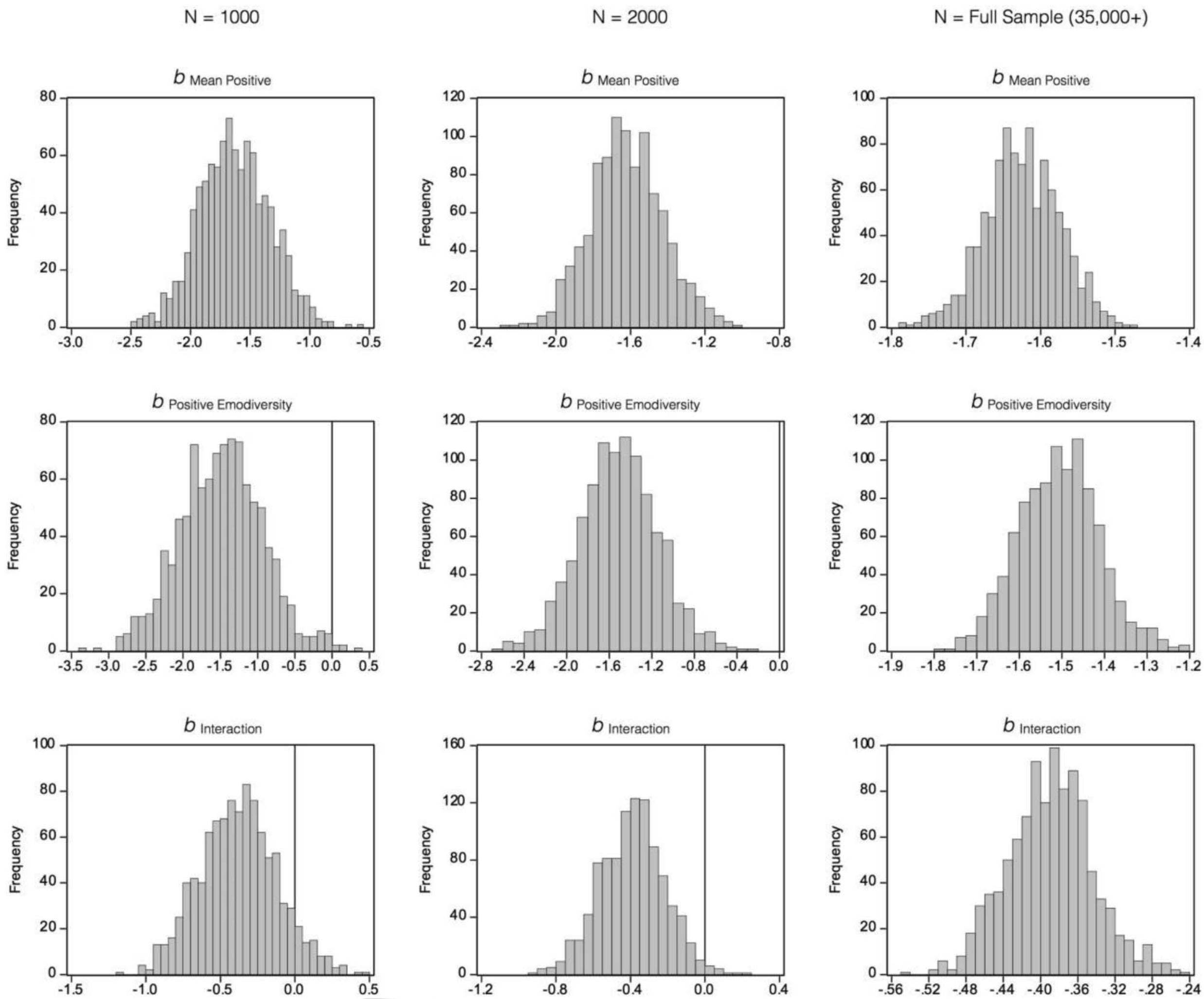

Figure 3. Distribution of regression coefficients for mean positive emotion, positive emodiversity and their interaction in 1,000 resamples with replacement of sizes 1,000, 2,000, and 35,844.

Christensen, & Benvenuto, 2001; Ciarrochi, Catuti, & Mayer, 2003; Demiralp et al., 2012; Kehner et al., 1993; Schwarz, 1990). Therefore, we expect that the effect of emodiversity would increase when including mean negative emotion and the interaction term in the regression. These results suggest that emodiversity is particularly beneficial when accounting for the tendency of people with high negative and global emodiversity scores to also have high mean negative emotion scores. Or stated differently, experiencing high levels of negative emotion is detrimental for health—but all things being equal, people seem better off experiencing moderate levels of fear, jealousy, and sadness together than only one of these three emotions at an extreme level.

Aside from the issue of theoretical grounding, Paulhus et al. (2004) also suggested that suppression effects are problematic when they fail to replicate in other samples. First, we note that the expected suppression effect replicates in recent research on emodiversity and health (Benson et al., 2017). Moreover, since the publication of our article (Quoidbach et al., 2014), the Belgian social security has included measures of emotions in some of their surveys. We were able to access the data from 8,820 new participants who completed a 19-item negative emotion scale[1] (compared to the 10 items in our original study) and for whom we have the mean number of visits to family doctors per year; the mean number of days spent in hospitals per year; and the mean defined daily dose (a typical indicator of medication consumption based on the average maintenance dose per day). As in our original Study 2, we also obtained the average costs to the Belgian Social Security of these expenses for each participant per year.

First, the positive relationship between negative emodiversity and physical health replicated in this new independent dataset. Specifically, negative emodiversity was negatively related to visits

[1] Unfortunately, only three distinct positive emotions were assessed, making less meaningful the examination of the diversity of positive emotion.

Table 2
Sobel Test Coefficients (Z) and Associated p Values Testing Whether Mean Positive and Negative Emotion Acted as Suppressor Variables in the Different Regression Models of Study 2 of Our Original Paper (Quoidbach et al., 2014)

•••	Positive emodiversity	Negative emodiversity	Global emodiversity
Doctor's visits	.33 (p = .74)	4.63 (p < .001)	PE: –.19 (p = .85) NE: 5.20 (p < .001)
Doctor costs for SS	.24 (p = .81)	5.26 (p < .001)	PE: –.42 (p = .67) NE: 5.74 (p < .001)
Days spent hospitalized	–1.23 (p = .22)	5.14 (p < .001)	PE: .25 (p = .80) NE: 5.75 (p < .001)
Hospital costs for SS	–1.21 (p = .23)	2.61 (p < .01)	PE: –.67 (p = .50) NE: 2.90 (p < .01)
Mean DDD	.66 (p = .51)	5.21 (p < .001)	PE: –.05 (p = .96) NE: 4.41 (p < .001)
Prescription drugs costs for SS	–1.45 (p = .15)	5.63 (p < .001)	PE:–1.03 (p = .30) NE: 4.35 (p < .001)

Note. PE = mean positive emotion; NE = mean negative emotion; SS = Social Security; DDD = defined daily dose.

to the doctor (ß = −.13, t = 6.43, r_{partial} = −.07, p < .001), doctor-related costs to Social Security (ß = −.12, t = 5.97, r_{partial} = −.06, p < .001), days spent at the hospital (ß = −.11, t = 5.25, r_{partial} = −.06, p < .001), hospital-related costs to Social Security (ß = −.09, t = 4.24, r_{partial} = −.05, p < .001), mean defined daily dose (ß = −.10, t = 4.84, r_{partial} = −.05, p < .001), and medication-related costs to Social Security (ß = −.12, t = 5.53, r_{partial} = −.06, p < .001) over and above mean negative emotion. Second, consistent with our original findings, the expected suppression effects also replicate, whereby the magnitude of the beneficial effect of negative emodiversity on health significantly increased when including mean negative emotion and the mean x emodiversity interaction in the regressions (all zs > 6.97, all ps < .001). In short, the suppression effects in our original article (Quoidbach et al., 2014) are supported by our theoretical account, and replicate both in a study by an independent team of researchers and a new large sample.

Conclusion

We appreciate the attention and thought devoted by Brown and Coyne (2017) to our research. Our study (Quoidbach et al., 2014) was the first to propose an operationalization of emodiversity, and we genuinely hope that future research will provide more and better ways to capture the diversity of human emotional life. Until then, the present in-depth examination suggests that our findings are statistically robust and replicable and reflect a theoretically grounded phenomenon with real-world implications.

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