Two presidential election cycles ago, I published “Does Diversity Pay? Race, Gender, and the Business Case for Diversity” in this journal (Herring 2009). In that research, I came to the conclusion that “diversity pays because businesses that draw on more inclusive talent pools are more successful. Despite the potentially negative impact of diversity on internal group processes, diversity has a net positive impact on organizational functioning” (p. 220). Moreover, I presented results that clearly ran counter to the claims of skeptics who argue that diversity and inclusion are harmful to businesses. Other scholars have reached similar conclusions using different data and methods (e.g., King et al. 2011; Levine et al. 2014; Nishii 2013; Singal 2014).

Conservative research centers, think tanks, and foundations have unleashed a full frontal assault on research that suggests any positives associated with diversity (Cokorinos 2003). I do not place Stojmenovska, Bol, and Leopold (2017) (hereafter SBL) in this category. Indeed, I believe they are providing a service to the discipline by attempting to verify and, when necessary, correct errors that happen in the research process. I thank them for uncovering coding errors in my analysis and for their service to the discipline in this regard. And while I appreciate such efforts, I believe some of SBL’s concerns are misplaced in this particular instance. Below, I will explain where I agree and where I disagree with SBL’s proposed alterations and conclusions.

RESPONSE TOSTOJMENOVSKA, BOL, AND LEOPOLD

Although it is not directly relevant to the question of whether diversity is still a good thing, I do need to clear up a statement made...
by SBL. They state that “[i]n our correspon-
dence with Herring, he did not offer a defini-
tive explanation” (p. 858) of missing values
and sample sizes. What they do not say is that
I offered no response to an inquiry. I have no
record of correspondence with SBL. I have
changed institutions, addresses, and e-mail
addresses. As I will detail, differences in
sample size between my analyses and theirs
arise from two sources: coding errors and dif-
f erences in treatment of missing data.

There is an issue where SBL and I agree:
“the 888888888888 problem.” As they suggest,
“the present case illustrates how a third group
of stakeholders—data producers—can con-
tribute to the quality and reproducibility of
social science research. In the NOS data . . .
the coding conventions used for missing val-
ues are conducive to errors, given that a com-
bination of negative and high positive values
(some of which fell within the possible range
of substantive codes) were used” (p. 865).
They are correct in pointing out that, because
of the coding scheme released by those col-
lecting the data, I erroneously coded some
firms as having $88,888,888,888 in sales rev-
ue or 888,888 customers. Some companies,
in fact, reported even higher revenue or num-
bers of customers. Removing these cases from
the analysis does lead to less statistical power.
Still, because I used listwise deletion in each
model, cases with the 888888 problem on one
dependent variable were not lost for the analy-
sis of the other dependent variables.

However, SBL and I disagree about the
extent of missing values on control variables
used in the analysis. For example, they use
different indicators of establishment size than
I do, which leads to a greater loss of cases than
the indicator I use. Apparently, they summara-
ize responses to two questions: (1) the num-
ber of full-time employees and (2) the number
of part-time employees. Instead, I coded the
midpoints of the employee size categories
variable called “strata,” which was the basis
for sampling business organizations of various
sizes and was provided by Dun and Brad-
street’s Information Services data file to pro-
vide accurate establishment size estimates for
all but 28 of the firms. In the original analysis,
I used single-imputation methods that assigned
these missing cases to the mean for establish-
ment size. When little data are missing (as I
assumed was the case in the original analysis),
single imputation provides a useful enough
and computationally efficient tool; however,
when the number of missing cases is exten-
sive, multiple imputation is more appropriate (Zhang 2016). In the updated analysis, I use
multiple imputation. For the top category
(5,000+ employees), I recoded this to be the
equivalent of the sum of full-time and part-
time employees for the establishment.

I also derive estimates of company size in
a manner that differs from that of SBL. For
companies with only one site, I code their
company size as being identical to their estab-
ishment size. When companies have multiple
sites, like SBL I use the response to a question
that asks how many full-time and part-time
employees the entire company has at all of its
locations. My method leads to 12 missing
cases. In the original analysis, I used single-
imputation methods that assigned these miss-
ing cases to the mean for company size. In the
updated analysis, I use multiple imputation.

The National Organizations Survey (NOS)
asked about firms’ racial and gender compo-
sitions in two different ways. NOS allowed
respondents to answer in terms of either per-
centages or numbers. When respondents
answered in raw numbers, percentage minor-
ity employees can be calculated by taking the
number of white employees and dividing by
the number of all employees, multiplying by
100, and then subtracting that number from
100. Similarly, gender composition (i.e., per-
centage female employees) can be calculated
by taking the number of female employees
and dividing by the number of all employees,
and multiplying by 100. As I suggested in the
original article, I top coded my AID-R indica-
tor at 25 (parity); I top coded my AID-G at 46
(parity). This leads me to have slightly differ-
ent ranges for these central independent vari-
ables than do SBL.

My coding differs substantially from SBL
on another control variable. SBL assign 121
cases to missing because of non-reporting on the state in which firms were located. In my original analysis, I erroneously assigned those cases to a residual coding category (West). I now use multiple imputation to assign a region for those cases.

Thus, I believe that after multiple imputation for four control variables, the appropriate Ns for the multivariable analyses for the various dependent variables should be 318 for sales revenue, 350 for number of customers, 470 for market share, and 485 for relative profitability. This is in contrast to the 239 for sales revenue, 270 for number of customers, 348 for market share, and 362 for relative profitability that SBL report.

My updated analysis is based on a smaller sample size and multiple imputation of four control variables (i.e., region, company size, establishment size, and company age) but yields results similar to my original analysis. In the original article, I reported results from one-tail hypothesis testing (consistent with directional hypotheses) and reported results as “marginally” significant (p < .1) and “statistically” significant (p < .05 or p < .01). In this version, I report p-values based on two-tail testing and include the standard errors in the regression tables.

Table 1 presents means and percentage distributions of various business outcomes of establishments by their levels of diversity. Average sales revenues are associated with higher levels of racial diversity: the mean revenues of organizations with low levels of racial diversity are roughly $52.3 million, compared with $323.9 million for organizations with medium levels and $808.9 million for those with high levels of diversity. The same pattern holds for sales revenue by gender diversity: the mean revenues of organizations with low levels of gender diversity are roughly $45.2 million, compared with $302.9 million for those with medium levels and $639.7 million for those with high levels of diversity.

Higher levels of racial and gender diversity are also associated with greater numbers of customers: the average number of customers for organizations with low levels of racial diversity is 23,100. This compares with 587,000 for organizations with medium levels of racial diversity and 475,000 for those with high levels. The mean number of customers for organizations with low levels of gender diversity is 13,300. This compares with 123,500 for those with medium levels of gender diversity and 576,700 for those with high levels.

Table 1 also shows that businesses with medium and high levels of racial and gender diversity are more likely to report higher than average percentages of market share than are those with low levels of racial and gender diversity. A similar pattern emerges for organizations reporting higher than average profitability. Less than half (47 percent) of organizations with low levels of racial diversity report higher than average profitability. In contrast, about two thirds of organizations with medium and high levels of racial diversity report higher than average profitability. Also, organizations with high levels of gender diversity (62 percent) are more likely to report higher than average profitability than are those with low (45 percent) or medium (58 percent) levels of gender diversity.

Another alternative analysis that SBL offer has to do with transformations of the data. There are ongoing debates about whether and how to transform data (e.g., Feng et al. 2014; Hoaglin, Mosteller, and Tukey 1983; Manning and Mullahy 2001; Miller 1984). Although Mosteller and Tukey’s (1977) “bulging rule” provides a starting point for possible transformations to correct nonlinearity, there is no consensus about right or wrong. Several analysts provide reasons for transforming data (e.g., Box and Cox 1964; Hinkley 1977; Osborne 2010). Others point out the disadvantages of doing so (e.g., Feng et al. 2014; Manning and Mullahy 2001; Miller 1984). Few would suggest that we transform observed variables just because they do not follow a normal distribution. Most would consider it wrong to transform data just to get higher correlations. I am not aware of any who would suggest the use of transformations that reduce the correlation
Table 1. Means and Percentage Distributions for Business Outcomes of Establishments by Levels of Racial Diversity and Gender Diversity

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Racial Diversity Level</th>
<th>Gender Diversity Level</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low (&lt;10%)</td>
<td>Medium (10 to 24%)</td>
</tr>
<tr>
<td>Percent in Racial or Gender Diversity Category</td>
<td>44.1</td>
<td>19.4</td>
</tr>
<tr>
<td>Mean Sales Revenue (in millions)</td>
<td>52.3</td>
<td>323.9</td>
</tr>
<tr>
<td>Mean Number of Customers (in thousands)</td>
<td>23.1</td>
<td>587.0</td>
</tr>
<tr>
<td>Percent with Higher than Average Market Share</td>
<td>46.3</td>
<td>62.8</td>
</tr>
<tr>
<td>Percent with Higher than Average Profitability</td>
<td>46.9</td>
<td>63.3</td>
</tr>
</tbody>
</table>
between the dependent variable and the central independent variables. Nevertheless, SBL suggest transforming predictor variables because they are not normally distributed. Doing so, however, would substantially reduce the apparent link between the dependent variables and diversity and at the same time increase the correlation between diversity and the control variables.

SBL provide evidence that assumptions of the linear model are violated without logarithmic transformations of company size and establishment size. They also suggest that these transformations improve the fit of the model. As I mentioned earlier, they apparently use different indicators of establishment size and company size than I do. I do not pursue logarithmic transformations for two reasons. First, I performed a Breusch-Pagan/Cook-Weisberg test for heteroscedasticity for the relationship between each of the logged dependent variables and company size (both logged and unlogged) and establishment size (both logged and unlogged). These tests suggested that although there was some heteroscedasticity, taking the logarithm of company size and establishment size actually made this issue worse rather than better. In other words, although SBL’s suggestion to log two independent variables and the dependent variables reduces heteroscedasticity and improves model fit, it does not do so as much as adding just the logarithmic transformation to the dependent variables, as I have done.

A second reason for not using the logged version of company size is that it is inappropriate when using multiple imputation. Recent research by von Hippel (2013:113) suggests that when imputing a skewed variable under a normal model, it is better to do so without making transformations, because such “transformation can yield substantial bias if the transformed variable is not close to normal.”

When the dependent variable itself is highly skewed, as it is in the case of two of the dependent variables in my analysis, it is appropriate to transform the dependent variables rather than the independent variables. To generate the sales revenue variable, I took the natural logarithm of sales revenue (variable o9 in the original dataset) plus some small number (.01) divided by 100,000 (rather than 1,000,000 as stated in the original article). To generate the number of customers variable, I took the natural logarithm of the number of customers (variable o8 in the original dataset) plus some small number (.01) divided by 1,000. I added a small number (.01) so as not to lose additional cases just because of the logarithmic transformations, as the log of 0 is undefined and would create missing cases even when the firm reported real values. Adding .01 does not change the substantive interpretation (e.g., $1000 + .01 = 1000.01$). Other small numbers less than 1 (e.g., .1, .001, .05) could also be added without changing the substantive interpretation. I selected 100,000 and 1,000 as the divisors for presentation purposes, so that the number of significant digits for display would not be too large or too small.

A TEST OF EIGHT HYPOTHESES

In contrast to SBL’s claim that I was making arguments in the original article, I was testing hypotheses that are consistent with theoretical claims from varying perspectives. My original analysis tested eight hypotheses about diversity and business performance and found support for seven of them (at \( p < .1 \)):

Hypothesis 1a: As racial workforce diversity increases, a business organization’s sales revenues will increase.

Hypothesis 1b: As gender workforce diversity increases, a business organization’s sales revenues will increase.

Hypothesis 2a: As racial workforce diversity increases, a business organization’s number of customers will increase.

Hypothesis 2b: As gender workforce diversity increases, a business organization’s number of customers will increase.

Hypothesis 3a: As racial workforce diversity increases, a business organization’s market share will increase.
Hypothesis 3b: As gender workforce diversity increases, a business organization’s market share will increase.

Hypothesis 4a: As racial workforce diversity increases, a business organization’s profits relative to its competitors will increase.

Hypothesis 4b: As gender workforce diversity increases, a business organization’s profits relative to its competitors will increase.

Table 2 shows the relationship between racial and gender diversity in establishments and logged sales revenue, logged number of customers, estimates of relative market share, and estimates of relative profitability. Model 1 shows that racial diversity and gender diversity are positively related to sales revenue ($b = .066$, $p < .01$ and $b = .017$, $p < .05$, respectively). Diversity accounts for roughly 10 percent of the variance in sales revenue. These results are fully consistent with Hypotheses 1a and 1b.

Model 2 shows that racial and gender diversity are also significantly related to the number of customers. As racial and gender diversity in establishments increases, their number of customers also increases ($b = .052$, $p < .01$ and $b = .071$, $p < .05$, respectively). Diversity accounts for 13 percent of the variance in number of customers. These results are consistent with Hypotheses 2a and 2b.

Model 3 in Table 2 shows a positive relationship between racial diversity and estimates of relative market share ($b = .009$, $p < .05$). However, gender diversity in establishments is not systematically related to relative market share ($b = .004$, $p = .12$). These results are consistent with Hypothesis 3a but not with Hypothesis 3b.

Finally, Model 4 displays the relationship between racial and gender diversity and estimates of relative profitability ($b = .009$, $p < .05$ and $b = .006$, $p < .05$, respectively). As diversity increases, estimates of relative profitability also increase. The results are statistically significant and consistent with Hypotheses 4a and 4b.

But do these results hold up once alternative explanations are taken into account? Table 3 presents the same relationships as Table 2, but it includes controls for alternative explanations. Model 1 of Table 3 presents the relationship between racial and gender diversity in establishments and logged sales revenue. In Model 1, the relationship between racial diversity and sales revenue remains significant ($b = .064$, $p < .01$), net of controls for legal form of organization, company size, establishment size, organization age, industrial sector, and region. However, the relationship between gender diversity and sales revenue is no longer statistically significant at $p < .05$ ($b = .017$, $p = .08$). Combined, these factors account for 25.5 percent of the variance in sales revenue. The results in Table 3 provide support for Hypothesis 1a (i.e., as a business organization’s racial diversity increases, its sales revenue will also increase) but they are not inconsistent with Hypothesis 1b.

Model 1 of Table 3 examines alternative explanations of sales revenue. Net of all other factors, sole proprietorships have significantly lower sales revenues than do other legal forms of business, and firms providing business services have lower sales revenues than do other types of firms, on average. Model 1 also shows that logged sales revenues increase significantly as establishment size increases and as organizations age.

The standardized coefficients for this model (not reported in Table 3) show that a one standard deviation increase in racial diversity produces a .255 standard deviation increase in sales revenue. Furthermore, the relationship between racial diversity and logged sales revenue is stronger than the impact of establishment size (Beta = .198) and organization age (Beta = .206). Gender diversity is also important to sales revenue (Beta = .103), net of controls. Therefore, not only is diversity related to sales revenue, but it is among the most important predictors.

Model 2 in Table 3 presents the relationship between racial and gender diversity in establishments and number of customers. The relationships between racial diversity and number of customers and gender diversity and number of customers remain statistically
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sales Revenue</td>
<td>Customers</td>
<td>Market Share</td>
<td>Profitability</td>
</tr>
<tr>
<td>Racial Diversity</td>
<td>.066** (.013)</td>
<td>.052** (.017)</td>
<td>.009* (.004)</td>
<td>.009* (.004)</td>
</tr>
<tr>
<td>Gender Diversity</td>
<td>.017* (.008)</td>
<td>.071* (.011)</td>
<td>.004 (.002)</td>
<td>.006* (.003)</td>
</tr>
<tr>
<td>Constant</td>
<td>.132 (.297)</td>
<td>4.212** (.420)</td>
<td>3.361** (.093)</td>
<td>3.361** (.097)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.097**</td>
<td>.130**</td>
<td>.017*</td>
<td>.021*</td>
</tr>
<tr>
<td>N</td>
<td>318</td>
<td>350</td>
<td>471</td>
<td>486</td>
</tr>
</tbody>
</table>

Note: Coefficients are unstandardized.

*p < .05; **p < .01 (two-tailed tests).
### Table 3. Regression Equations Predicting Sales, Number of Customers, Market Share, and Relative Profitability with Racial and Gender Diversity and Other Characteristics of Establishments

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Model 1 Sales Revenue</th>
<th>Model 2 Number of Customers</th>
<th>Model 3 Market Share</th>
<th>Model 4 Relative Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Racial Diversity</td>
<td>.064** (.013)</td>
<td>.052** (.017)</td>
<td>.008* (.004)</td>
<td>.007+ (.004)</td>
</tr>
<tr>
<td>Gender Diversity</td>
<td>.017+ (.010)</td>
<td>.050** (.012)</td>
<td>.002 (.003)</td>
<td>.005+ (.003)</td>
</tr>
<tr>
<td>Proprietorship</td>
<td>-1.441* (.648)</td>
<td>-.063 (.802)</td>
<td>-.231 (.187)</td>
<td>-.162 (.198)</td>
</tr>
<tr>
<td>Partnership</td>
<td>-.801 (.760)</td>
<td>-.279 (.880)</td>
<td>.019 (.207)</td>
<td>.282 (.215)</td>
</tr>
<tr>
<td>Public Corporation</td>
<td>-.705 (.634)</td>
<td>.914 (.793)</td>
<td>.178 (.170)</td>
<td>.213 (.177)</td>
</tr>
<tr>
<td>Private Corporation</td>
<td>-.799 (.544)</td>
<td>-.593 (.662)</td>
<td>.016 (.153)</td>
<td>.026 (.159)</td>
</tr>
<tr>
<td>Company Size</td>
<td>.000 (.000)</td>
<td>.000 (.000)</td>
<td>.000 (.000)</td>
<td>.000 (.000)</td>
</tr>
<tr>
<td>Establishment Size</td>
<td>.001** (.006)</td>
<td>.000 (.000)</td>
<td>.000 (.000)</td>
<td>.000 (.000)</td>
</tr>
<tr>
<td>Organization Age</td>
<td>.020** (.006)</td>
<td>.012+ (.007)</td>
<td>.001 (.002)</td>
<td>.001 (.002)</td>
</tr>
<tr>
<td>Agriculture</td>
<td>-1.939+ (1.048)</td>
<td>.729 (1.371)</td>
<td>-.187 (.324)</td>
<td>-.027 (.345)</td>
</tr>
<tr>
<td>Mining</td>
<td>2.150 (1.723)</td>
<td>-3.792* (1.921)</td>
<td>-.268 (.518)</td>
<td>-.372 (.553)</td>
</tr>
<tr>
<td>Construction</td>
<td>-.116 (.596)</td>
<td>.224 (.770)</td>
<td>-.087 (.198)</td>
<td>.010 (.211)</td>
</tr>
<tr>
<td>Transport./Comm.</td>
<td>.403 (.669)</td>
<td>.716 (.824)</td>
<td>.175 (.184)</td>
<td>.268 (.193)</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>.630 (.692)</td>
<td>1.135 (.789)</td>
<td>.137 (.205)</td>
<td>-.076 (.223)</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>-.245 (.422)</td>
<td>4.187** (.556)</td>
<td>.079 (.125)</td>
<td>-.121 (.132)</td>
</tr>
<tr>
<td>F. I. R. E.</td>
<td>.143 (.635)</td>
<td>1.601* (.759)</td>
<td>-.233 (.179)</td>
<td>.061 (.194)</td>
</tr>
<tr>
<td>Business Services</td>
<td>-1.697+ (.675)</td>
<td>3.365** (.944)</td>
<td>.368+ (.197)</td>
<td>-.056 (.210)</td>
</tr>
<tr>
<td>Personal Services</td>
<td>-.432 (.526)</td>
<td>1.346+ (.708)</td>
<td>.219 (.161)</td>
<td>.115 (.169)</td>
</tr>
<tr>
<td>Entertainment</td>
<td>-2.116+ (1.269)</td>
<td>1.699 (1.671)</td>
<td>-.155 (.453)</td>
<td>-.089 (.483)</td>
</tr>
<tr>
<td>Professional Services</td>
<td>-.619 (.502)</td>
<td>.090 (.586)</td>
<td>.155 (.153)</td>
<td>-.010 (.157)</td>
</tr>
<tr>
<td>Midwest</td>
<td>.519 (.389)</td>
<td>-.427 (.475)</td>
<td>-.015 (.115)</td>
<td>-.153 (.123)</td>
</tr>
<tr>
<td>South</td>
<td>.035 (.348)</td>
<td>-.973* (.452)</td>
<td>-.048 (.104)</td>
<td>-.006 (.112)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.535 (.684)</td>
<td>3.974** (.875)</td>
<td>3.325** (.205)</td>
<td>3.375** (.217)</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.251**</td>
<td>.305**</td>
<td>.031*</td>
<td>.019</td>
</tr>
<tr>
<td>( N )</td>
<td>318</td>
<td>350</td>
<td>470</td>
<td>485</td>
</tr>
</tbody>
</table>

**Note:** Coefficients are unstandardized. Standard errors are in parentheses. For the dummy (binary) variable coefficients, significance levels refer to the difference between the omitted dummy variable category and the coefficient for the given category.  
+\( p < .10 \); *\( p < .05 \); **\( p < .01 \) (two-tailed tests).
significant \( (b = .052, p < .01 \) and \( b = .050, p < .01 \), respectively), controlling for legal form of organization, company size, industrial sector, and region. A one-unit increase in racial diversity increases the percentage of customers by 5 percent; a one-unit increase in gender diversity increases the number of customers by over 5 percent. The overall model accounts for 30.5 percent of the variance in number of customers. These results fully support Hypotheses 2a and 2b (i.e., as a business organization’s racial and gender diversity increase, its number of customers will also increase).

Model 2 also examines alternative explanations of number of customers. Again, the relationship between racial diversity and number of customers (Beta = .152) is stronger than the impact of company size, establishment size, and organization age. Gender diversity is also more highly related to number of customers, maintaining a statistically significant relationship (Beta = .221) net of controls. These results again suggest that diversity is among the most important predictors of number of customers.

Model 3 in Table 3 shows that the relationship between racial diversity \( (b = .008, p < .05 \) and market share remains statistically significant when controlling for legal form of organization, company size, and industrial sector. The relationship between gender diversity \( (b = .002, p = .55 \) and relative market share remains non-significant. Model 3 accounts for 3.1 percent of the variance in estimates of market share. These findings are consistent with Hypothesis 3a (i.e., as a business organization’s racial diversity increases, its market share will also increase), but they do not support Hypothesis 3b. Racial diversity (Beta = .10) is the most important predictor of relative market share.

Model 4 in Table 3 reports the positive relationship between racial diversity and relative profitability \( (b = .007, p = .085 \) and between gender diversity and relative profitability \( (b = .005, p = .094 \). Model 4 explains 1.9 percent of the variance in estimates of relative profitability. These results are not inconsistent with Hypothesis 4a (i.e., as a business organization’s racial diversity increases, its profits relative to competitors will also increase), and they are not inconsistent with Hypothesis 4b (i.e., as a business organization’s gender diversity increases, its profits relative to competitors will also increase). Both racial diversity (Beta = .086) and gender diversity (Beta = .091) are among the most important predictors of relative profitability.

**SUMMARY AND CONCLUSION**

Is diversity still a good thing? As I mentioned earlier, I regret making the coding errors in my original analysis. I am grateful to Stojmenovska and colleagues (2017) for their service to the discipline and for helping me get the analysis right. Still, I believe that my updated analysis provides support for the idea that there are relationships between diversity and various dimensions of business performance, such as sales revenue, number of customers, market share, and profits relative to competitors, even when controlling for other important factors. Despite having less statistical power in the updated analyses, the results continue to provide support for the seven hypotheses that received some support in the original analyses (at \( p < .1 \)). Moreover, my research has helped inspire newer research with more recent data and in other types of organizations that has borne out the link between diversity and positive organizational outcomes. Yes, diversity is still a good thing, but not just because it is related to business outcomes. Diversity is also a good thing because it reinforces the belief that everyone—no matter their race, ethnicity, gender, sexuality, or religion—deserves an equal opportunity. This message is even more important now than it was two presidential elections ago.

**References**


