Identifying varieties of nationalism: A critique of a purely inductive approach

Maureen A Eger | Mikael Hjerm

Department of Sociology, Umeå University, Umeå, Sweden

Correspondence
Maureen A. Eger, Department of Sociology, Umeå University, 90187 Umeå, Sweden.
Email: maureen.eger@umu.se

Funding information
The Swedish Research Council for Health, Working Life and Welfare (Forskningsrådet för hälsa, arbetsliv och välfärd [FORTE]), Grant/Award Number: 2016-07177;
Marianne and Marcus Wallenberg Foundation (Marianne och Marcus Wallenbergs Stiftelse [MMW]), Grant/Award Number: 2014.0019

Abstract
Most theoretical and empirical approaches to nationalism not only distinguish between ethnic and civic notions of national belonging but also differentiate national identity from national hubris, pride, and attachment. In this research note, we examine recently published research on nationalist sentiments in the United States that takes a different approach. The study in question, ‘Varieties of American Popular Nationalism’ by Bonikowski and DiMaggio (2016), has already become quite influential in the field and has the potential to change how we conceptualise and operationalise attitudes about the nation. In this research note, we revisit its analytical strategy and exploratory methods. We ask two questions. First, does this study allow us to draw conclusions about American nationalism? To answer this, we replicate the original model and then execute additional postestimation analyses, whose results undermine the study’s main conclusions. Second, we investigate whether judicious revisions to the study’s model generate results that would lead us to the article’s same conclusions. The 385 additional models lend no support. Based on this evidence, we argue that the original study’s conclusions stem from a misinterpretation of its latent class
analysis (LCA), as our own analyses demonstrate that there is no empirical basis for its claims.

**KEYWORDS**
civic nationalism, ethnic nationalism, latent class analysis, nationhood/national identity, patriotism, research methods

1 | INTRODUCTION

In ‘Varieties of American Popular Nationalism’, Bonikowski and Dimaggio (hereafter B&D) offer a timely portrait of the nationalist sentiments that characterise the American population. B&D argue that identifying differences in how Americans understand what it means to be ‘American’ is essential for making sense of the contentiousness that animates contemporary national politics. They rely on Brubaker’s (1996:10) description of nationalism: ‘a heterogeneous set of “nation”-oriented idioms, practices, and possibilities that are continuously available or “endemic” in modern cultural and political life’ (Bonikowski & DiMaggio, 2016:952).

B&D’s theoretical starting point leads them to analyse American nationalism by combining indicators of national identity with measures of national patriotism, chauvinism and identification with the nation—all concepts that previous research has shown are distinct. Already cited extensively, this purely inductive approach could be pathbreaking for the field of nationalism. If the results produced from its analysis are valid, this approach should change trajectory of the field. Given these stakes, we present a thorough examination of the analytical strategy and exploratory methods that animates their approach. Our analysis has two components. First, we examine if Bonikowski and DiMaggio (2016) have revealed meaningful patterns in the data that allow us to draw conclusions about varieties of nationalist sentiment. Second, we investigate whether judicious revisions to their model generate results that lead us to their same conclusions. Before doing so, in the next section, we provide an overview of national identity, patriotism, chauvinism and identification.

2 | ATTITUDES ABOUT THE NATION

The scholarly literatures on national identity and nationalism in political science, sociology, as well as political philosophy have adopted a dichotomous understanding of national identity. Often described as a Janus-face conceptualisation, the most common version is the distinction between ethnic and civic (Kohn, 2017 [1944]; Smith, 1991; Brubaker, 1992). An ethnic conception of national belongingness includes ascribed characteristics, specifically ancestry, country of birth, and historic cultural traditions such as a country’s dominant religion. A civic conception of nationhood emphasises an adherence to common values that binds people together and upholds the country’s institutions. Consistent with this theoretical division, empirical studies of nationalist sentiments have typically treated indicators of nationalism as civic or ethnic (Esses et al., 2005; Hjerm, 1998; Jones & Smith, 2001a, 2001b). The majority of scholarship embraces, at least implicitly, the parsimony of the ethnic-civic distinction. Indeed, the major debate in the contemporary empirical literature has not been whether or not the dichotomy is theoretically sound (cf. Kymlicka, 2001) but instead how to operationalise it (Huddy & Khatib, 2007; Larsen, 2017; Reeskens & Hooghe, 2010). This has led to a number of different empirical strategies, both deductive and inductive (see Larsen, 2017 for a review). Recent efforts have produced cross-national evidence of the theoretical dichotomy (Larsen, 2017; Reeskens & Hooghe, 2010).

As noted by Reeskens and Hooghe (2010: 593): ‘The distinction between civic and ethnic citizenship concepts dominates the study of citizenship and nationhood’. Nonetheless, scholarship also identifies other forms of related
yet distinct attitudes about the nation. First, national identification is a feeling of closeness to the nation. Most empirical studies rely on unidimensional scales that do not distinguish between conceptions of nationhood, where the source of belonging should be ethnic or civic, but instead capture the strength of identification with the nation (e.g., Green et al., 2011; Hjerm & Schnabel, 2010; Staerklé et al., 2010). Often referred to as patriotism, a second sentiment is national pride, which is described as positive attachment to and pride in one’s country (Kosterman & Feshbach, 1989) or affection for the nation (Esses et al., 2001). A third is national hubris (Bonikowski & DiMaggio, 2016), which is more typically referred to as national chauvinism (e.g., Citrin et al., 2001) or nationalism (e.g., Huddy & Khatib, 2007; Kosterman & Feshbach, 1989). Chauvinism differs from patriotism in that it goes beyond love of country and ‘reflects a perception of national superiority and an orientation towards national dominance’ and is most similar to Adorno et al.’s (1950) ethnocentrism (Kosterman & Feshbach, 1989:271). Citrin et al. (2001:75) call this ‘extreme and bounded loyalty, the belief in the superiority of one’s country, right or wrong’.

Scholarship that has investigated the relationships among these political sentiments consistently finds that they represent distinct attitudinal constructs (e.g., Davidov, 2011; Esses et al., 2001; Wagner et al., 2012). This body of research includes studies of American attitudes, a number of which rely on the broad range of indicators of attitudes towards the United States that first appeared in the 1996 General Social Survey (GSS). For example, Citrin et al. (2001) use exploratory and confirmatory factor analyses to distinguish between patriotism and chauvinism (i.e., national pride and national hubris) as well as ethnic and civic notions of national identity. Using structural equation models (SEM), Huddy and Khatib (2007) find that a three-factor solution best fits the 1996 data, concluding that national identity is an attitudinal dimension distinct from nationalism (i.e., national hubris) and national pride. These studies are consistent with Kosterman and Feshbach’s (1989:272) finding that nationalism (i.e., national hubris) and patriotism (i.e. national pride) are separate constructs despite being correlated ($r = 0.28$). Each of these studies links these different forms of political sentiments to other political attitudes and behaviour.

3 | ‘VARIETIES OF NATIONALISM’

In ‘Varieties of American Popular Nationalism’, Bonikowski and DiMaggio (2016) reject both the classic two-dimensional approach to nationality identity and the notion that it is distinct from other kinds of political sentiments. To find support that not only enables the conflation of theoretically distinct concepts under the umbrella of nationalism but also to motivate a purely inductive analytical strategy, the authors lean on Brubaker’s (1996:10) description of nationalism as ‘a heterogeneous set of “nation”- oriented idioms, practices, and possibilities that are continuously available or “endemic” in modern cultural and political life’ (Bonikowski & DiMaggio, 2016: 952). Arguably, B&D have taken Brubaker out of context, because when examining nationalism and patriotism, he makes clear that these are different concepts and that patriotism is not a dimension of nationalism (Brubaker, 2004).

Nevertheless, B&D’s theoretical starting point—the notion that nationalism can be many things—is consistent with their analytical strategy and application of latent class analysis (LCA). They combine this tool ‘with an unprecedentedly broad range of indicators’ from the 2004 GSS (pg. 951), meaning they include all the variables that have become standard in analyses of national sentiments: seven identity indicators; 10 patriotism indicators; five chauvinism indicators; and one indicator of identification.

Although these variables have been used previously, they have not been analysed in this way. The authors agree that there are four political sentiments that contribute to different varieties of nationalism. However, the authors have, in a sense, freed the items from the four concepts they were intended to measure. This is extra problematic because the number of items in each of the four batteries varies considerably. To use a cooking analogy, it appears the recipe for American nationalism is 10-parts pride, seven-parts identity, five-parts hubris and one-part identification. The authors interpret the results of their analysis to mean that four varieties of
nationalism exist in the United States and go on to label them restrictive, disengaged, ardent, and creedal. They report nearly identical findings for analyses of 1996 GSS and 2012 Growth from Knowledge (GfK) Custom Research survey data.

4 | OUR ANALYTICAL STRATEGY

Our first step is to replicate their analyses. In our second step, we re-analyse their results following standard procedure for interpreting LCA models and additional analyses appropriate for models with a large number of variables. This includes presenting multiple indicators of absolute model fit. We then examine the relative fit of the various cluster solutions. In our third and final step, we use LCA to test 385 alternative versions of their models using fewer indicators from each category of political sentiment.

LCA allows for the identification of mutually exclusive, latent classes of individuals who share similar characteristics on a given set of categorical indicators (McCutcheon, 1987). For example, LCA can help reveal diagnostic categories based on a variety of medical symptoms, find specific types of consumption based on individual consumer data, or identify attitudinal profiles among survey respondents. Compared to other statistical methods, the interpretation of results from LCA is not always straightforward. Ram and Grim (2009:571) explain: ‘...there is not a deterministic set of rules to follow when selecting the best model (see Hair & Black, 2000). Rather, model selection is an art—informed by theory, past findings, past experience, and a variety of statistical fit indices’.

5 | REPLICATING THEIR MODEL

We limit our replication to a reanalysis of the 2004 GSS data, specifically 23 indicators—from four batteries designed to capture national identification, identity, hubris and pride—as well as 10 sociodemographic covariates. These data constitute the primary focus of B&D’s original analysis, and the only fit indices they report come from the 2004 survey. We use the data and syntax files B&D provide in the supplemental materials to replicate Table B1, also found in their supplemental materials. Like the authors, we use Stata to clean the data and Latent GOLD 5.0 for LCA. We run K1-K8 models, where K1 is a one-cluster solution and each subsequent model categorises respondents into additional classes.

During our replication, we found some discrepancies between what is reported in the article and what is presented in Table B1. B&D report a sample of 1077 cases including cases with missing values on nationalism indicators. In the supplemental materials, they refer to this as ‘Sample 2’. However, the authors’ Latent GOLD syntax included in the replication package suggests that they used the restricted sample, ‘Sample 1’. Other discrepancies between the text and syntax deal with correlating residuals and using weights. To reproduce the number of parameters and degrees of freedom for each cluster solution, we relied on the sample that excludes all missing values (N = 830) and we did not correlate residuals or use weights. Nevertheless, the authors make clear that different sample sizes and alternative model specifications do not substantively change their results. We agree. We ran their model on all three samples, with different specifications, and these decisions have no meaningful impact on model fit statistics.

Table 1 is our replication of the authors’ LCA cluster solutions and relative goodness-of-fit statistics. Our log likelihood (LL) and Bayesian information criterion (BIC) estimates deviate slightly from those reported in Table B1. At first glance, this suggests an issue of local maximas, when the estimation algorithm converges on a local maximum solution instead of on the global maximum solution. To check for this, we ran our models with a number of different starting values and the results are stable, at least for K1-K5. Where our statistics diverge, we have included the authors’ findings below in parentheses. We stress, though, that these differences are minor (i.e., these are essentially the same results).
### Table 1 Replication of ‘Varieties of Nationalism’ LCA solutions (B&D’s Table B1)

<table>
<thead>
<tr>
<th></th>
<th>Log-likelihood</th>
<th>BIC (LL)</th>
<th>N of parameters</th>
<th>Degrees of freedom</th>
<th>Classification error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 class</td>
<td>−19075.71</td>
<td>38648.81</td>
<td>74</td>
<td>756</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>(−19174.91)</td>
<td>(38847.20)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 classes</td>
<td>−17920.66</td>
<td>36668.05</td>
<td>123</td>
<td>707</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>(−18029.66)</td>
<td>(36886.06)</td>
<td></td>
<td></td>
<td>(0.042)</td>
</tr>
<tr>
<td>3 classes</td>
<td>−17483.11</td>
<td>36122.31</td>
<td>172</td>
<td>658</td>
<td>0.070</td>
</tr>
<tr>
<td></td>
<td>(−17545.69)</td>
<td>(36247.47)</td>
<td></td>
<td></td>
<td>(0.062)</td>
</tr>
<tr>
<td>4 classes</td>
<td>−17142.97</td>
<td>35771.38</td>
<td>221</td>
<td>609</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>(−17182.20)</td>
<td>(35849.83)</td>
<td></td>
<td></td>
<td>(0.063)</td>
</tr>
<tr>
<td>5 classes</td>
<td>−16997.89</td>
<td>35810.56</td>
<td>270</td>
<td>560</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>(−16996.18)</td>
<td>(35807.14)</td>
<td></td>
<td></td>
<td>(0.058)</td>
</tr>
<tr>
<td>6 classes</td>
<td>−16867.29</td>
<td>35878.72</td>
<td>319</td>
<td>511</td>
<td>0.090</td>
</tr>
<tr>
<td></td>
<td>(−16908.66)</td>
<td>(35961.45)</td>
<td></td>
<td></td>
<td>(0.083)</td>
</tr>
<tr>
<td>7 classes</td>
<td>−16799.66</td>
<td>36072.80</td>
<td>368</td>
<td>462</td>
<td>0.075</td>
</tr>
<tr>
<td></td>
<td>(−16753.31)</td>
<td>(35980.1)</td>
<td></td>
<td></td>
<td>(0.059)</td>
</tr>
<tr>
<td>8 classes</td>
<td>−16704.67</td>
<td>36212.17</td>
<td>417</td>
<td>413</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>(−16650.33)</td>
<td>(36103.5)</td>
<td></td>
<td></td>
<td>(0.086)</td>
</tr>
</tbody>
</table>

Note: We include the authors’ original findings in parentheses where our results differ.

# 6 Re-examining the Results

## 6.1 Absolute fit

In many types of statistical analyses, it is necessary to assess absolute fit—or how well the data corresponds to the fitted model. The most widely used statistic in LCA is $L^2$, which measures the likelihood that the observed cell frequencies match the expected frequencies.

In sparse models, however, $L^2$ does not approximate a Chi-square distribution and therefore should not be used to assess model fit (e.g., Langeheine et al., 1996). Sparse models are models in which many observed cells are empty due to either a large number of variables, a large number of response categories, and/or a small $N$. B&D’s model easily meets the criteria for sparseness: they use 23 indicators, each with 4–5 possible response categories, combined with 10 covariates and sample size of less than 1000.

In Table 2, we report a variety of statistics that help us determine absolute fit. The first group includes Chi-squared statistics. Due to the sparseness of the data, we cannot rely on the $L^2$ outright; however, we can bootstrap the analyses (e.g., Langeheine et al., 1996; Vermunt & Magidson, 2004). We use the standard setting in Latent GOLD (Vermunt & Magidson, 2005), which means 500 bootstraps per model, and report bootstrapped $p$ values for both $L^2$ and $X^2$.

Results for $L^2$ reveal non-significant $p$ values for all models. This suggests that a one-class solution ($K_1$) fits the data well enough. In other words, there are not enough patterns among these 23 indicators to identify more than one type of American nationalism. However, bootstrapping reveals significant $p$-values for $X^2$, which implies an ostensibly different story. Consistently significant $p$-values means that significant levels of associations remain unaccounted for regardless of how many classes we introduce. Some argue that the bootstrapped $X^2$ is more reliable than bootstrapped $L^2$ in sparse models (van Kollenburg et al., 2015), but both sets of $p$-values indicate that the authors’ preferred four-cluster solution does not capture the associations among the observed variables.
<table>
<thead>
<tr>
<th>Chi-squared statistics</th>
<th>Total bivariate residuals (TBVR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TBVR</td>
</tr>
<tr>
<td><strong>L²</strong></td>
<td><strong>L² reduction</strong></td>
</tr>
<tr>
<td>1 class</td>
<td>38148.66</td>
</tr>
<tr>
<td>2 classes</td>
<td>35838.55</td>
</tr>
<tr>
<td>3 classes</td>
<td>34963.46</td>
</tr>
<tr>
<td>4 classes</td>
<td>34283.17</td>
</tr>
<tr>
<td>5 classes</td>
<td>33993.00</td>
</tr>
<tr>
<td>6 classes</td>
<td>33731.82</td>
</tr>
<tr>
<td>7 classes</td>
<td>33596.54</td>
</tr>
<tr>
<td>8 classes</td>
<td>33406.56</td>
</tr>
</tbody>
</table>
Another indicator of absolute model fit is the total bivariate residuals (TBVR), which is still robust in sparse models (Kollenburg et al., 2015). TBVR represents the sum of associations between each pair of observed variables in the model unaccounted for by the classes. Given that the goal of LCA is to produce a solution that accounts for all associations in the data, in a perfectly fitting model, TBVR would be zero. Using real world data makes this unlikely, but in a model that fits well, TBVR should be non-significant. Table 2 shows that all TBVRs are significant, indicating that none of the cluster solutions adequately account for associations between variables. The TBVR for the four-cluster solution is 1706, which is extremely high considering the total number of bivariate correlations is 736 (23*22 items + 23*10 covariates). The critical values (CV) tell us how small the TBVR should be in order to be non-significant. The difference between the TBVRs and these CVs are substantial in all models.

The individual bivariate residuals (BVR) further demonstrate the poor model fit. There is no absolute threshold for a single BVR, but 1.96 is commonly used though the makers of Latent GOLD recommend 1.0. In the K4 model, B&D have 244 BVRs that are greater than 1 and 171 that are greater than 1.96. In fact, they have 43 BVRs that are greater than 10. Masyn (2013) argues that a poorly fitting model is characterised by BVRs that are in ‘notable excess’ of 1%–5%. Almost 25% of the BVRs are above 1.96. This means that the four-class solution does not account for the associations among the observed variables.

It is more difficult to judge the absolute fit of sparse models, with many indicators and response categories, than more parsimonious models. Nevertheless, it remains a mandatory first step in evaluating LCA models. Here, we provided two sets of fit statistics that are appropriate for sparse models. Both make clear that their model does not fit.

6.2 | Relative fit

‘Evaluations of relative fit do not tell us anything about absolute fit so keep in mind even if one model is a far better fit to the data than another model, both could be poor in overall goodness of fit’ (Masyn, 2013:567 italics in original). B&D only report indices associated with relative fit, which merely suggests that they have picked the least poorly fitting model. Yet, our additional analyses actually indicate that the authors have not selected the best cluster solution (out of a number of very poor solutions) after all.

The authors’ decision to rely on BIC is reasonable. However, research shows that in sparse models the Bootstrap Likelihood Ratio Test (BLTR) performs better than both BIC and Akaike information criterion (AIC) (Nylund et al., 2007; Tein et al., 2013). The BLTR compares the bootstrapped log likelihood of the K-1 and the K cluster solution. If fit does not improve with an additional cluster, the p-value will be greater than 0.05. Table 3 show that the K5 solution is a significant improvement over the K4 solution. In fact, each additional class up to K8 is a significant improvement

<table>
<thead>
<tr>
<th>Bootstrap likelihood ratio test (BLRT)</th>
<th>Cluster classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>−2LL diff</td>
<td>p value</td>
</tr>
<tr>
<td>1 class</td>
<td>—</td>
</tr>
<tr>
<td>2 classes</td>
<td>2310.11</td>
</tr>
<tr>
<td>3 classes</td>
<td>875.09</td>
</tr>
<tr>
<td>4 classes</td>
<td>680.28</td>
</tr>
<tr>
<td>5 classes</td>
<td>290.17</td>
</tr>
<tr>
<td>6 classes</td>
<td>261.18</td>
</tr>
<tr>
<td>7 classes</td>
<td>135.27</td>
</tr>
<tr>
<td>8 classes</td>
<td>189.98</td>
</tr>
</tbody>
</table>
over the previous K-1 model. This pattern implies that the four-cluster solution is not best and is another indication that model fit is poor.

To exhaust all possibilities, we run one final postestimation analysis of cluster classification. If the model fits the data well, LCA predicts cluster membership for the observed individuals. Entropy $R^2$ measures classification accuracy and varies between 0 and 1, where higher entropy values reflect better classifications of individuals to classes (Granado, 2015). A rule of thumb is that the entropy should be greater than 0.8 (Ram & Grimm, 2009). Applying this, we note that the $K_4$ solution does a good job in assigning individuals to classes, but so do all of the $K_2$-$K_8$ models. This demonstrates, again, that the four-cluster solution does not have the best relative fit, as the $K_4$ cluster solution does not do a better job predicting class membership than any other solution.

7 | TESTING THEORETICALLY SIMILAR, NON-SPARSE MODELS

In our third and final step, we test non-sparse versions of B&D’s model, which necessitates decreasing the number of variables used. We contend that if these four types of attitudes actually underlie varieties of nationalism, then models that include far fewer indicators of each aspect should fit the data well and yield the same number of clusters. This strategy avoids sparseness but also avoids biasing the results, as there are 10 indicators of national pride while only one indicator of national identification.

We run 350 models that each includes the same measure of national identification and three additional variables representing national identity, national pride and national hubris. These models comprise every possible combination of a four-variable model. For each, we allow for up to eight clusters and identify the best solution based on the first to have a $p$-value above 95%. If no solution reaches that threshold, we code the model as having no best solution. We also collect information about the four-cluster solution, regardless of which solution is best.

Table 4 shows the frequencies of best cluster solutions based on $p$ values, revealing that a four-cluster solution has the best relative fit in only 14% of the models (see also Figure 1). The three-cluster solutions most often have the best relative fit, but only a quarter of the time. Two-cluster solutions come in second place and ‘no best solution’ third. Table 4 also reports average goodness-of-fit statistics for these cluster solutions. Across models, no solution yields an average reduction in $L^2$ that is even close to what would be considered indicative of reasonable fit. In this case, the highest is 56% (seven classes), while the average $L^2$ reduction for the four-cluster solutions is 50.13%.

Given national identification (i.e., ‘How close to do you feel to America?’) is included in each of the 350 models tested, we wondered if this variable contributes to these models’ poor absolute fit, especially considering it was only one of 23 variables treated as equal in B&D’s sparse models. Thus, we eliminated that variable and generated a 10%
random sample of the 350 models. Fit statistics from three-variable models ($N = 35$) are reported in Table 5 (see also Figure 1). Results make clear that, without national identification, these models fall apart completely. Taken together, these results show that non-sparse versions of the underlying model neither fit the data nor confirm the presence of four varieties of American nationalism.

### CONCLUSION

With their research, Bonikowski and DiMaggio (2016) advanced an innovative approach to the study of nationalism. Although the aim of this article is not to offer a theoretical critique, their conceptualisation of nationalism had...
consequences for subsequent methodological decisions. The authors themselves refer to these 23 variables as unprecedentedly broad, and, while they mean this in regard to the study of nationalism, we have been unable to locate another article that uses so many ordinal variables in LCA.

Does this broad range of indicators help us identify varieties of American nationalism? Our replication reveals that Bonikowski and DiMaggio’s model does not fit the data. When we test the absolute fit of their model, something they did not do, we show unequivocally that they advanced a non-fitting model. We also revisit their claims about relative fit and cluster solutions. They maintain that the K4 solution, meaning four varieties of nationalism, has the best relative fit, but using methods that are appropriate for sparse models, we find no support for this. Last, when we test non-sparse versions of their model, we do not find any evidence of four distinct attitudinal profiles. Based on this combined evidence, we argue that their conclusions stem from a misinterpretation of their LCA analysis, as our own analyses demonstrate that there is no empirical basis for their claims.

What does this mean for future research? To be clear, we believe that LCA can be a very useful method to identify empirical patterns, especially when theoretically motivated. As noted by Ram and Grimm (2009:571), model selection is informed by a combination of theory, previous empirical results, a variety of fit indices. Similarly, Petersen et al. (2019) argue that not only model fit statistics but also factors like theoretical expectations, ease of interpretation, size and parsimony should motivate choosing a LCA cluster solution. We believe parsimony should also be a consideration when researchers select variables for their model. If that is not possible, researchers must remember that sparse models require additional steps (i.e., postestimation analyses) that if ignored may lead us to judge poorly fitting models as acceptable.

Although we find error in their execution, we commend Bonikowski and DiMaggio’s motivation to understand what nationalism means in everyday life. To accomplish this, we need new ways of measuring theoretically and practically relevant attitudes, which implies efforts on multiple fronts. First, the research focused on the quantitative measurement and explanation of particular attitudes must be in better dialogue with scholarship that relies on qualitative methods and thick descriptions of everyday life. Second, like Bonikowski and DiMaggio provided, we need new country-case studies. Third, all future empirical efforts must maintain dialogue with theory.

ACKNOWLEDGEMENTS
This research was supported by the Marianne and Marcus Wallenberg Foundation (Marianne och Marcus Wallenbergs Stiftelse [MMW]) Grant No. 2014.0019 and the Swedish Research Council for Health, Working Life and Welfare (Forskningsrådet för hälsa, arbetsliv och välfärd [FORTE]) Grant No. 2016-07177.

ORCID
Maureen A Eger https://orcid.org/0000-0001-9023-7316
Mikael Hjerm https://orcid.org/0000-0003-4203-5394

ENDNOTES
i Despite its inclusion in the 2004 GSS, they exclude the item regarding the importance of American ancestry from their analysis. They do not give a reason, but previous research suggests it is not as important for Americans as it is for other nationalities (Reeskens & Hooghe, 2010).

ii The authors correlate a number of residuals to overcome the issue of local maxima and report this as an additional four-class solution in the last row of Table B1.

iii It seems reasonable to ask whether this level of scrutiny is necessary considering other types of analysis, such as ordinary least squares (OLS) regression, are not judged similarly. For instance, low $R^2$s are not cited as a reason not to trust OLS coefficients. However, OLS only tells us about relationships between an independent and dependent variable, which is fundamentally different from an analysis that tests for the existence of a latent construct. The goal of an LCA analysis is to account for all the covariance among variables in the model, making a test of absolute fit critical. This is consistent with how researchers use structural equation modelling (SEM). A model that does not fit the data is discarded.
REFERENCES


