An Analysis of ANES Items and Their Use in the Construction of Political Knowledge Scales*

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Valid comparisons of group scores on additive measures such as political knowledge scales require that the conditional response probabilities for individuals on the observed items be invariant across groups after controlling for their overall level of the latent trait of interest. Using a multi-group confirmatory factor analysis of knowledge items drawn from American National Election Studies, we find that the scales used in recent research are not sufficiently invariant for valid comparisons across a host of theoretically important grouping variables. We demonstrate that it is possible to construct valid invariant scales using a subset of items and show the impact of invariance by comparing results from the valid and invalid scales. We provide an analysis of differential item functioning (DIF) based on grouping variables commonly used in political science research to explore the utility of each item in the construction of valid knowledge scales. An application of the vanishing tetrad test suggests it is more appropriate to conceive of these items as effects of a latent variable rather than cause or formative indicators. These results suggest that models attempting to explain apparent knowledge gaps between subgroups have been unsuccessful because previously constructed scales were validated by fiat.

1. Introduction

Political knowledge is a central construct in a number of theories, including voting behavior (Macdonald, Rabinowitz, and Listhaug 1995; Palfrey and Poole 1987), political discussion (Ahn, Huckfeldt, and Ryan 2010; Huckfeldt 2001; Morehouse Mendez and Osborn 2010), persuasion (Zaller 1992), decision making (Lau and Redlawsk 2001), media consumption (Prior 2005; Young 2004), perception of racial bias (Pantoja and Segura 2003), and motivated reasoning (Lodge and Taber 2000; Taber and Lodge 2006). Research testing these theories typically assumes that survey questions measuring an awareness of officeholders and candidates can be combined with questions about party platform positions and ideological placements to create a valid scale on which sub-populations can be compared.

Recent research has sought to determine the degree to which aspects of the survey instrument limit the validity of knowledge scales (Davis and Silver 2003; Gibson and Caldeira 2009; Mondak 2001; Mondak and Anderson 2004; Prior and Lupia 2008). An unaddressed question is whether the measurement properties of such scales are sufficiently invariant across groups to justify valid comparison of sub-populations. While consideration of measurement invariance is not new to political science (e.g., Alvarez and Nagler 2004; Clinton, Jackman, and Rivers 2004, Davidov 2009; Stegmueller 2011), we could find no instance in the literature where a rigorous test has been applied to support the assumption that political knowledge scales can be the basis for valid cross-group comparisons—despite the theoretic importance of political knowledge to the discipline.

The purpose of this study is to fill that void by assessing the extent to which recently published political knowledge scales constructed from American National Election Studies (ANES) data can be used to make valid comparisons. We rely on a well-developed literature in

the social sciences on measurement invariance spanning three decades (Byrne, Shavelson, and Muthen 1989; Horn and McArdle 1992; Meredith 1993; Millsap and Yun-Tein 2004; Muthen and Christoffersson 1981; Vandenberg and Lance 2000; Widman and Reise 1997) and readily available software to estimate the necessary models (Arbuckle 2009; Jöreskog and Sörbom 2006; Muthen and Muthen 2010). We show that recently used knowledge scales are not valid for group comparisons across a host of theoretically important grouping variables. Using a subset of knowledge items, we then provide a set of new scales that demonstrate measurement invariance for most grouping variables and compare the invalid full scales and the new invariant scales, demonstrating that commonly employed knowledge scales can produce misleading estimates of differences in knowledge between subgroup. We also examine the extent to which individual knowledge items are non-invariant across groups, providing guidance for future research by helping identify the items that are most problematic for the constructions of measurement invariant knowledge scales. Finally, we use a vanishing tetrad test to assess the nature of the measurement model underlying political knowledge items. The test suggests it is more appropriate to conceive of these items as effects of a latent variable rather than cause or formative indicators.

2.   The Centrality of Political Knowledge

Scholars agree widely that political knowledge shapes the behavior of citizens in a democracy. The surplus of information that citizens require to participate in politics coupled with a scarcity of time and effort places a premium on political expertise (Downs 1957). Political participation requires individuals to draw from a series of political cognitions (e.g., beliefs, attitudes, associations) that rest in long-term memory. For political experts, these cognitions are well organized and contain a great deal of information spanning a wide range of policy domains

(Luskin 1987). Consequently, political stimuli bring relevant information automatically to active memory (Lodge and Taber 2000; Taber and Lodge 2006). For political novices, relevant information may come less quickly to mind or may be absent entirely from long-term memory. Hence, political experts behave quite differently than nonexperts in a number of circumstances.

Research shows that political expertise increases the propensity to vote and the extremity of policy attitudes (Palfrey and Poole 1987). Experts' opinions are more stable and less susceptible to influence (Lodge and Taber 2000; Taber and Lodge 2006). Moreover, expertise is a self-reinforcing condition as it governs subsequent information intake through media consumption decisions (Prior 2005) and discussion patterns (Huckfeldt 2001; Morehouse Mendez and Osborn 2010).

There is considerable debate over whether encyclopedic political knowledge is necessary for meaningful participation. One camp argues that citizens can overcome a dearth of knowledge by utilizing cues and shortcuts (Freedman, Franz, Goldstein 2004; Franz, Freedman, Goldstein and Ridout 2007; Lupia 1994). Others argue that citizens lacking some baseline knowledge cannot properly apply such cues (Lau and Redlawsk, 2001), which leads to suboptimal decision making (Bartels 1996). Nonetheless, knowledge scales are the most commonly employed indicator of political sophistication and political awareness (Lodge, McGraw, and Stroh 1989; Luskin 1987; Delli Carpini and Keeter 1993; Zaller 1992).

Determinants of Knowledge

A large body of research focuses on the determinants of political knowledge. Thus, scholars seek to compare the knowledge levels of various groups. Scholars have widely accepted that cognitive ability and interest increase political knowledge (Luskin 1990; Highton 2009). Research suggests that education, on the other hand, has little or no effect on political knowledge

after controlling for its determinants (Luskin 1990; Highton 2009). There is more controversy about the other potential determinants of knowledge. Luskin (1990) finds no effect of age on knowledge, while Lau and Redlawsk (2008) find that age increases factual information while decreasing information processing abilities. Likewise, Luskin (1990) finds no media exposure effect, while Prior (2005) finds that media choice has a large effect on knowledge levels.

A recurring finding in the literature is that women are less knowledgeable than men (Delli Carpini and Keeter 1996, 2000; Frazer and McDonald 2003; Verba, Burns, and Schlozman 1997). Scholars have attributed this knowledge gap, in part, to women's lower propensity to guess (Lizotte and Sidman, 2009; Mondak and Anderson 2004), interviewer effects (McGlone, Aronson, and Kobryonowicz 2006), and gender-based differences on the strength of association between personal characteristics and knowledge (Dow 2009). The gap remains after controlling for these considerations and the estimated size of the gap varies greatly between studies. The content of knowledge scales is also under scrutiny as a growing body of literature suggests that the substance of knowledge batteries is biased toward male conceptions of politics while excluding the considerations most important to many females. Recent research suggests that the knowledge gap disappears on issues of practical relevance to women such as social services, government benefits, and female representation in government (Dolan 2011; Stolle and Gidengil 2010). If the political wants and needs of men and women differ, then relevant political considerations should be expected to vary along gender lines as well.

Thus, there are strong methodological and theoretical barriers that may inhibit the direct comparison of knowledge levels of various groups using standard knowledge batteries. The inconsistent findings for the determinants of knowledge, such as gender, may stem from this measurement barrier. Before we can make meaningful comparisons between groups on such a

scale, we need to be sure that the scale is invariant between groups. In the absence of measurement invariance, observed effects are confounded with group-specific differences in the measuring devices.

Measuring Knowledge

Due to the centrality of political expertise to the discipline, measurement of knowledge has been a chief concern (Delli Carpini and Keeter 1993; Luskin 1987; Mondak 1999; Mondak 2001). Knowledge is typically assumed to be an unobserved variable that can be measured by summing an individual's correct responses to a battery of survey items. These items come in several varieties, including general ideological placements, issue placements, and objective knowledge items. Ideological placements ask respondents to place themselves on the seven-point left-right axis and to correctly identify positions of candidates and parties on the same scale (Delli Carpini and Keeter 1993; Dow 2009). Analogous issue-specific items are also included to measure respondents' knowledge of narrower policy domains. Objective knowledge questions tend to include items asking respondents to identify jobs of various politicians and the responsibilities of various government actors (Delli Carpini and Keeter 1993; Dow 2009).

Conclusions about relative knowledge levels of various groups can be sensitive to item format. Multiple choice items encourage guessing, which lowers item reliability (Delli Carpini and Keeter 1993, 1184). Moreover, some groups of people are more likely to guess than others (Rapoport 1979). Thus additive scales featuring multiple choice questions will, on average, overestimate the knowledge of people and groups prone to guessing. Researchers can avoid differential guessing by discouraging don't know responses (Mondak 2001).

Open-ended items feature their own problems. First, they are more difficult to code. Partially correct responses are often treated as incorrect, which prevents discriminating between partially-informed and uninformed citizens (Mondak 1999). It is also difficult to discourage don't know responses in such formats (Gibson and Caldeira 2009; Mondak 2001). Yet, past work suggests that multiple choice and open-ended items perform equally well in terms of item discrimination and difficulty (Delli Carpini and Keeter 1993, 1191). Thus, commonly employed knowledge scales tend to use a mix of both formats.

Items as Reflective or Cause Indicators

There are several differing conceptualizations of how political knowledge can be measured. Much of the prior research cited above is based on the conceptual view that the level of political knowledge someone possesses can be 'tested' via survey questions in a manner analogous to an academic test. At the foundation of this view is the idea that political knowledge is similar to other forms of knowledge possessed by an individual. While the content of other various forms of knowledge differ, there are fundamental similarities on how it is acquired, stored, and accessed.

<<Figure 1 Here>>

From this measurement point of view, the amount of knowledge one possesses in a domain of life is an internal trait, or a latent variable, that is not directly observable (but is assumed to be sufficiently unidimensional because it is domain-specific). The latent trait can be measured by presenting questions from within that domain to a respondent. These observed indicators are a means of estimating levels of the latent trait. The item responses 'reflect' the level of knowledge (see Figure 1A.). Higher levels of knowledge in the domain increases the likelihood of a correct answer to any particular question, although the odds of a correct answer

will differ from question to question depending on the their respective difficulties. It would, for example, be easier to name the President than the speaker of the House. But we would expect someone with a greater level of political knowledge to have a higher likelihood of getting both correct compared to someone with a lower level of knowledge. This measurement model is commonly labeled an 'effects' model (Bollen and Bauldry 2011) in which the observed indicators reflect the latent trait. This is the measurement model that underlies factor analysis.

There is an alternative conceptualization in the literature.[1] Although it is not often stated explicitly as such, this view treats political knowledge items as 'causes' of political knowledge rather than the effects of an internal state or trait. Within this view, there are two subdivisions of measurement models. One is that the items are causes of the latent trait (cause model). The other is that items can be combined as a substitute for a latent trait (formative or composite model).

It is under this latter subdivision that indexes are constructed as composite measure to substitute for the latent variable.[2] As noted above, the common approach is to sum a set of dummy variable responses into a single score. At the limit, a single knowledge item is sometimes used as a predictor variable but composite indexes are more commonly utilized. The other causal approach is to treat several indicators as 'causes' of the latent variable rather than combining them into a composite index (see Figure 1B.). This allows for an estimate of error at the latent variable level. As we explain the next section, validity assessments of composites are problematic. We can, however, assess validity under both the effect or cause indicator models.

Furthermore, the distinction between an effect and cause indicator models of political knowledge is important because the causal order between items and latent construct determines which measurement characteristics are appropriate for assessing validity (Bollen and Lennox 1991).

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Validity Assessment for Cause and Effect Indicators

Substantial work has been done over the past two decades on methods to judge whether indicators are best considered causes or effects of the latent variable. Work has also proceeded in methods to assess the measurement validity of cause indicators. As noted above, Bollen (2011) distinguishes between causal indicator models and composite (formative) indicator models. A composite variable, such as an index that is a linear combination of items, is assumed to reflect perfectly the level of political knowledge because of two strong assumptions: measurement error is not considered for the items and the index error variance is also assumed to be zero. Indicators of composite variables have been called 'formative indicators' in the past (Fornell and Bookstein 1982). We can test the assumption that the disturbance term for such an index is zero.

Bollen (2011) points out that because these indicators do not necessarily represent a unidimensional construct, it may not make sense to assess empirically their measurement validity because they are validated by fiat. He observes that if composite indicators are convenient ingredients used to form a linear composite variable, then it is not clear that assessments of validity apply to composites. Similarly, the measurement validity of a single item cannot be determined.

In contrast to a composite variable, the validity of multiple cause indicators of a latent variable can be assessed. This type of indicator also requires strong assumptions, however, about their measurement quality: they too are assumed to be measured without error at the item level. This is an untenable assumption in most situations, according to Edwards and Bagozzi (2000). Because the indicators are exogenous to the model, the error term is at the latent-variable level rather than at the item level. This latent variable disturbance term represents all the other causes omitted from the model. A common way to validate a causal indicator is to assess the strength of

its relationship to the latent variable it creates by examining the squared correlation coefficient and the structural coefficient (Bollen 2011) between the item and the latent variable.

This approach is similar to what is utilized to assess the validity of effect models, for which valid comparisons require that the measurement properties of the scale are invariant across groups. It is possible to analyze the measurement properties of such items using Item Response Theory (IRT). IRT has received attention from political scientists in recent methodological texts (Jackman 2008) and it has been applied to the gender gap in knowledge, but rarelyfor knowledge scales more generally. Of note, Lizotte and Sidman (2009) tested 122 items from 10 ANES surveys and found apparent observed gender differences in knowledge are confounded by the failure to obtain cross-gender measurement invariance. They did not, however, report any combination of items that do obtain invariance. We extend that study by exploring a number of item subsets and grouping variables.

Validity and Testing for Measurement Invariance

Shadish, Cook and Campbell (2002) define construct validity as the result of consistent operational definitions. If each operational instance (survey item) is of the same underlying construct, then the same causal relationship should result, regardless of how an outcome is operationally defined. If this result fails to be observed, this means that the operations are not in fact equivalent, and they tap into different constructs and, consequently, into different causal relationships.

For scale development with effect indicators, aspects of construct validity can be tested rigorously by assessing measurement invariance. We would contrast this approach with one that validates a scale by fiat. The definition of measurement invariance is based on the conditional probabilities of a correct answer, given the individual's common factor score (Millsap and Yun-

Tein 2004). Specifically, the conditional response probabilities for individuals on the observed items should be invariant across groups after adjusting for any differences in their overall level of political knowledge, which we will refer to as the "latent trait of interest" or the common factor. In other words, there should be "local independence" for the items such that there is no *group x item* interaction after partialling out the trait of interest. If such an interaction exists, the item is said to exhibit "differential item functioning" or DIF, which is often labeled "item bias" in testing situations.

Ackerman (1992) describes the basis of item bias as unintended multidimensionality. A "nuisance" dimension intrudes on the measurement occasion and is responsible for the *group x item* interaction that is observed after partialling out the trait of interest. As this nuisance dimension is distributed unequally between sub-groups, its effect introduces the item bias into the scale. The nuisance dimension can be one of a variety of factors, such as differences in item salience, prior experience, or socialization. A rigorous test of item bias is accomplished by assessing measurement invariance. Scales that are non-invariant are not sufficiently unidimensional for valid cross-group comparisons because the underlying constructs are not distributed uniformly across groups. In practical terms, a scale that is not sufficiently unidimensional cannot accurately reflect a person's performance in a single score, such as a sum or a mean value.

The model to test measurement invariance can be expressed in terms of an underlying *latent response variable* for each observed indicator, and a *latent trait* (or factor) that is of substantive interest – political knowledge in this case. The latent response variable represents the observed indicator and the latent trait represents the overall level of knowledge as measured by the scale.[3] Each dichotomous observed indicator X is related to an underlying continuous latent

response variable, X^*, such that the item is observed to be answered correctly if that latent

response variable exceeds a certain threshold, τ_x.

$$X = 1, \text{ if } X^* \geq \tau_x, \text{ otherwise } X = 0 \tag{1}$$

The latent response variables (X^*) underlying the items are then used in a multi-group

confirmatory factor analysis model to estimate the measurement and latent trait parameters.

The resulting Mplus one-factor model with a probit link is:

$$P(X = 1 \mid \eta) = \Phi\left[(-\tau_x + \lambda_x \eta)\theta^{-1/2}\right] \tag{2}$$

where η is the latent trait of interest (political knowledge), τ_x is the item threshold, λ_x is

the item loading and θ is the residual variance, which is typically standardized to 1.0 (Muthen

and Muthen 2010). A one-factor model is used here because prior substantive research has

assumed that the political knowledge scale is sufficiently unidimensional and thus an

individual's knowledge can be summarized by a single value. The single value is either an

average score or a summated score based on the number of correct answers. These values are

then averaged within groups and the observed group means are the basis for some type of

regression analysis.

In contrast to the observed mean, the expected value of the underlying latent response

variable X^* for the reference and non-reference groups can be expressed as:

$$E\left(X^*_{reference}\right) = 0 \tag{3}$$

$$E\left(X^*_{non-reference}\right) = \lambda \, \kappa_\eta \tag{4}$$

where κ_η is the mean of the latent trait or factor, η. The latent factor mean is fixed to zero

for the reference group and freely estimated in the non-reference group. Similarly, the factor

loading, λ, is assumed to be invariant across groups (Muthen and Asparouhov 2002; Brown 2006).

Measurement invariance is tested by constraining the loading (λ) and threshold parameters (τ) to be equal across sub-populations. The additional model misfit created by those constraints is assessed using a robust chi-square difference test ($\Delta \chi^2$) between nested models as the more restricted model is compared to a model that permits the parameters to vary between the groups.[4]

It can also be seen in the equations above why meaningful comparisons of observed means require invariance across groups for both the thresholds and loadings for the items that comprise the scale. Otherwise, observed mean differences are confounded with group differences in the measurement properties of the items used to construct the political knowledge scale (Millsap and Yun-Tein 2004). For example, the failure to obtain invariance for the factor loadings indicates the latent trait is defined differently in the various groups and they are qualitatively dissimilar (Meredith 1993). When the loadings are found to be invariant but thresholds are not, then the trait is defined consistently across groups. But it is measured using a group-specific metric and valid comparisons cannot be made between sub-populations on either the latent response variable means or, more importantly, the observed means. That is because a necessary condition for valid comparisons on the observed means is for measurement invariance to hold on the underlying latent response variables (Millsap and Yun-Tein 2004). In other words, if an item is be found to be non-invariant, a consequence is that the latent response variable is not in the same metric across the groups so that its variance should not be compared between sub-populations (Asparouhov and Muthen 2006).

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It should be noted that some authors invoke "partial invariance" (Byrne, Shavelson and Muthen 1989) and suggest that while valid comparisons cannot be made on observed means, they can be made on the latent variable group means (κ_η) if "most," but not all, of the loadings and thresholds are invariant. There are several limitations of this view. First, there is no general agreement what constitutes" most." Second, it does not in any way resolve the validity problem for comparisons of the observed means or measures.

Readers familiar with item response theory may note that the model expressed in equation 2 is functionally equivalent to a two-parameter normal ogive IRT model (Muthen and Asparouhov 2002). An advantage of the formulation presented here is that it allows for tests of specific measurement parameters across groups.

Differentiating Between Cause and Effect Indicators

Because methods for assessing measurement validity differ depending on whether knowledge items are conceived as cause or effects, we need a way to adjudicate between the two models. It is often unclear, however, whether indicators should be best considered causes or effects of a latent variable. There are two avenues to address this question. One is the application of substantive knowledge and theory. The other is an empirical assessment of each model to see which fits the data better.

Conceptual checks on whether an item should be considered a cause indicator are related to issues of face validity. The first is the extent to which the item corresponds to the theoretical definition of the latent variable. The second is the whether it can be argued a change in the item would cause a change in the latent variable, or if a change in the latent variable would cause a change in the observed indicator (Bollen and Bauldry 2011). It is clear that the items do correspond to political knowledge. It is less clear which direction the causal arrow goes. It could

be argued that correct candidate placement along an ideological continuum would add to the level of political knowledge. On the other hand, it is equally plausible to argue that higher levels of political knowledge would make it more likely to be able to pinpoint a candidate's ideological position correctly. So, an empirical check might provide additional evidence on which to make a judgment.

One empirical implication for composites and cause indicators is that by definition they are required to be composed of a census of indicators. Omitting an indicator is omitting part of the construct (Bollen and Lennox 1991). So, different amalgamations of causal items create different variables that are not comparable. A political knowledge variable, for example, that includes a measure of the identity of the speaker of the House is not the same variable as one that excludes this measure. This trait makes such measures idiosyncratic and generally not comparable across studies. This conceptualization is in contrast to the effect indicator model. If all possible questions in a domain are considered the universe of indicators of the latent trait, it is appropriate to sample from within the domain. This property emerges because equally reliable effect indicators of a unidimensional concept are essentially interchangeable. Different samples of items that cover the range of the domain are expected to obtain comparable trait level estimates on average. By this property, political knowledge items appear to function as effects indicators: Delli Carpini and Keeter (1993, 1202) show that small subsets of knowledge items capture a large proportion of variance in scales comprised of all available items in their data set.

Moreover, recent developments in structural equation modeling provide a direct test to differentiate cause and effect indicators (Bollen and Ting 1993, 2000; Hipp and Bollen 2003; Hipp, Bauer, and Bollen 2005). The available empirical test involves pairs of covariances that are implied by two different models that incorporate the differing views of the relationship

between the indicators and the latent variables. A "vanishing tetrad difference test" (VTT) (Bollen and Ting 2000) compares the two models.

Briefly, a tetrad is the difference between two pairs of item covariances implied by a measurement model involving four items (Equation 5), where $\sigma_{gh}\sigma_{ij}$ is the product of the implied covariances of items g and h and i and j.

$$\tau_{ghij} = \sigma_{gh}\sigma_{ij} - \sigma_{gi}\sigma_{hj}, \tag{5}$$

Because the covariances from an effects model (where the observed indicators depend on the latent variable) can be expressed completely in terms of factor loadings and the latent variable variance, these tetrads have an expected value of zero. In other words, the tetrads are expected to disappear in an effects model ($\tau_{ghij} = 0$). In contrast, the tetrads from a cause indicator model (formulated as a multiple indicators multiple causes (MIMIC) model[5] (Hauser and Goldberger 1971) see Figure 2), are not expected to vanish by equaling zero because the covariances across items do not cancel out.

<<Figure 2 here>>

A tetrad model difference test statistic, distributed as a chi square variate, is available to test the hypothesis that the cause indicator MIMIC model significantly fits the data better than the effect indicator model. If the test produces a non-significant chi square, then the model with the most vanishing tetrads (the effects) is preferred. A significant chi square suggests otherwise as the less restricted (cause) model has a better fit. This test has been implemented in a SAS macro (Hipp, Bauer and Bollen 2005) that compares the tetrads in the two model implied covariance matrices.

We can use this method to decide between the cause and effects models of political knowledge, in order to inform our subsequent validity tests. First, though, we detail the data we will use.

3.   Data and Measures

For this analysis, we rely on Dow's (2009) knowledge battery, which includes respondents to the 1992, 1996, 2000, and 2004 American National Election Studies (ANES).[6] The battery is largely representative of the knowledge scales commonly employed in the discipline and includes general-ideology placements, policy-specific placements, and open-ended objective knowledge questions.

For each year, there are three general ideology items. The first equals one for the respondents who are able to place themselves on the seven-point liberal-conservative scale. The second is correct for those that place the Democratic presidential candidate at a more liberal position than the Republican candidate on the seven-point scale. The third is correct for respondents that place the Democratic Party at a more liberal position than the Republican Party.[7]

There are seven policy-specific placements for the 1992, 1996, and 2000 studies and eight policy-specific placements for the 2004 study. The policy-specific placements focus on four issues: 1) services and spending, 2) defense spending, 3) jobs and standard of living, and 4) abortion. The ANES asks respondents to identify the Democratic and Republican presidential candidates' position on each issue. The services and spending, defense spending, and jobs and standard of living items use seven-point scales while the abortion items use four-point scales.[8] The 2000 study is an exception where we collapse to a five-point scale all responses for the services and spending, defense spending, and jobs and standard of living items. Respondents are

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correct on these items if they place the Democratic candidate at a more liberal position than the Republican candidate. Respondents also place the two parties on each of these issues, though the 1992, 1996, and 2000 studies each omit one set of party-issue placements. In 1992 and 2000, the ANES does not include the abortion party placements and in 1996 it does not include the jobs and standard of living party placement. Hence, the 1992, 1996, and 2000 studies have seven policy-specific items while the 2004 study, which includes all four party placements, has eight policy-specific items.

There are four objective knowledge items for each study year, though the content of the items varies from year to year. Each open-ended item asks respondents to identify the political position held by a public figure. For example, all four years ask respondents to identify the position held by William Rehnquist. Those answering "Chief Justice of the Supreme Court" are correct. In addition to the Chief Justice item, 1992 and 1996 studies include items asking respondents to identify the vice president, the president of Russia, and the Speaker of the House. The 2000 study includes the Chief Justice item, as well as items regarding the British Prime Minister, the Senate Majority Leader, and the U.S. Attorney General. The 2004 study includes items regarding the Chief Justice, Vice President, British PM, and Speaker of the House.

The principal ANES investigators documented problems with the administration of some objective knowledge questions in recent surveys, particularly items that identify the chief justice and British PM (Krosnick, Lupia, DeBell, and Donakowski, 2008). In light of this report, we also test whether the inclusion of these questionable items interfere with valid scale construction.

To create the scales, we sum the number of correct responses for a respondent and divide by the total number of knowledge items from the study year. The denominator in the 1992, 1996, and 2000 studies is 14 and the denominator in the 2004 study is 15 for the full battery. [9] (The

item subsets used for each survey year are shown in Table A1 of the appendix.) Hence, we code respondents incorrect on an item if they refuse to answer or provide a "don't know" response.[10] The ANES includes a pre and post-election wave and we draw knowledge items from both waves. Thus, we drop those respondents who did not take part in both waves. Following Dow (2009), we restrict our sample to the ANES respondents who were not missing on any of Dow's explanatory variables and omit African Americans from the analysis.

We evaluate the validity of knowledge scales for group comparisons using grouping items commonly included in models of political knowledge, including gender (e.g., Delli Carpini and Keeter 1996, 2000; Dow 2009; Frazer and McDonald 2003; Verba, Burns, and Schlozman 1997) as well as age (e.g., Lau and Redlawsk 2008; Luskin 1990), education (e.g., Luskin 1990; Highton 2009) , income (e.g., Lambert et al. 1988), media use (e.g., Luskin 1990; Prior 2005), and political participation (e.g., Palfrey and Poole 1987). We compare age and income groups below the median value in a given year to those at or above the median. For education, we compare respondents with a college degree to those without a degree. We include four media-use grouping variables. The first three are binary measures indicating whether the respondent obtained campaign news from newspapers, radio, or television. The fourth asks the number of days in the last week the respondent watched TV news and separates the respondents below the median from those at or above the median. The participation variable separates those who participated in a recent campaign in some way (tried to influence others, attended meetings/rallies, worked for party/candidate, displayed sticker/button, donated money) from those who did not.

Analytic Plan

The analytic plan is to assess the measurement invariance of a political knowledge scale used in prior research and is based on the effect indicator model. If the full scale fails to obtain invariance across groups, we will search for a subset of items that will provide a more valid scale. Finally, we will check our model specification by conducting the tetrad test to determine whether it may be more appropriate to consider the invariant items as cause indicators. Part of the process necessary to carry out the tetrad test is the estimation of MIMIC models with these items. A useful byproduct of those models is a parameter estimate of the latent variable error term. If that disturbance term is significant, then the formative composite index assumption of errorless measurement is ruled out (Bollen and Bauldry 2011).

4.   Results

A Test of Measurement Invariance

To assess measurement invariance, we first estimate the non-invariance model, which is unidimensional and allows the loading and thresholds to vary by demographic group. The test of invariance is based on the degradation in model fit when the two sets of measurement parameters are constrained to be equal across groups.[11] Statistically significant differences in model fit suggest that measurement invariance fails as the misfit is large relative to the number of cross-group parameter constraints imposed. The results of tests of measurement invariance across the grouping variables are shown in Figure 3. Table A2 provides the results in tabular form.

<< Figure 3 here>>

The figure plots the p-value associated with the χ^2 test of change in model fit for the full and six-item scales by each grouping variable in each year. Points with values > .05 indicate that

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a scale is invariant with respect to the associated grouping variable, while points below this threshold indicate a scale's measurement-noninvariance and therefore its invalidity for comparisons across subgroups created by that grouping variable. The figure shows that measurement invariance is rejected for scales comprised of all items for almost all demographic grouping variables as the constraints lead to statistically significant degradation in model fit. The exceptions are participation in 1996, radio use in 2004, and television use in all years. As mentioned above, the ANES principle investigators noted coding errors in several objective knowledge questions. With one exception, excluding these questionable items had no effect on the substantive results, as the results from the 13-item scales in Figure 3 display. The lone exception is frequency of television viewership in 2004, in which the 13-item scale is invariant while the 15-item scale is not.

Figure 3 demonstrates that the full scales are not valid for group comparisons on most group indicators. We therefore also construct a new set of scales and in the figure, demonstrate their validity for group comparisons within each year. Table A1 lists the specific items used for each year, which were selected because together they produce scales that are invariant for many grouping variables while keeping the item content similar across years. Each scale includes two objective knowledge items, three issue placements, and one general ideological placement of the candidates. The six-item scales thus retain the diversity of items found in the full scales and the relative use of objective knowledge, issue placements, and general ideology placements are roughly proportional between the six-item and full scales. Furthermore, there is a core subset of items that is asked in every survey year. Nonetheless, we could not include all the same items in each year's scale, due to the inconsistencies in ANES items across years[12] and the ANES administration problems detailed by Krosnick et al. (2008). Yet, as we will discuss below, the

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inclusion or omission of any particular item would not change the substantive meaning of the scale, under the assumptions of an effect measurement model. For each year, the new six-item scales are sufficiently invariant on the basis of respondent gender, education, income, newspaper use, participation, radio use, and TV use, with a few year-specific exceptions.[13] The six-item scales are similarly invariant for frequency of TV use in 2004 and 1996, but not 2000 or 1992.

Table 1 shows that the new scales perform as well as the full scale in criterion tests of construct validity for the various ANES indicators of political participation, which constitute some of the most widely studied effects of political knowledge (e.g., Deli Carpini and Keeter 1996; Popkin and Dimock 1999; Verba, Schlozman, and Brady 1995. For a review of this literature, see Galston 2001). The table shows that the point-biserial correlations between 1) the full scales and the individual participation indicators and 2) the six-item scales and the individual indicators of participation are similar in magnitude and direction. Thus, the table suggests that these abbreviated scales can be useful for studying political knowledge, while avoiding the problem of measurement non-invariance. Moreover, the non-invariance findings suggest that the correlations between the full scales and the participation indicators are biased by some nuisance dimension. Thus, the similarity in correlations belies an important distinction between the two sets of scales. We therefore turn next to assessing the extent and direction of the bias.

<<Table 1 here>>

Measurement Non-invariance and Effect Size

The use of these commonly employed, but non-invariant knowledge scales can bias considerably the estimated differences between subgroups. To evaluate the effect that measurement invariance has on substantive findings, we compare bivariate effect sizes of various factors on political knowledge estimates.   Table 2 shows how measurement non-invariance

confounds estimates of effect size. The table shows the effect size estimates (Cohen's *d*) for group comparisons on the basis of dichotomous measures of gender, income, political participation and educational attainment. Here, the effect size inflation ranges from a low of 2 percent to as much as 13 percent. But there is also sizeable estimation *deflation* as it attenuates the effect sizes for gender and age in some years that range from a low of -13 percent to a maximum of -175 percent. These discrepancies are due to *item x group* interactions that are related to some unidentified nuisance dimension that interferes with the measurement instrument and artificially inflates or deflates the effect sizes.

<<Table 2 here>>

This analysis demonstrates that the influence measurement non-invariance has on the estimates of effect sizes is often substantial, but also varies widely depending on the year and the grouping variable under consideration. The important point is that there is no way to predict how effect size will be confounded by non-invariant measures in any particular situation and, therefore, no way to anticipate its direction or adjust for it.

<<Table 3 here>>

Table 3 provides another way to evaluate the consequences of non-invariance, by regressing the full scale on each of the grouping variables first without controlling for the invariant six-item scale and then after including the control.[14] If the non-invariant scale and the invariant scale we propose are essentially equivalent, then there should be no significant coefficients in the second model. If there are, however, significant coefficients in the second model for a given year, it indicates that the full scale is contaminated by a nuisance dimension associated with the grouping variable, but independent of political knowledge—thereby biasing full-scale estimates of political knowledge differences. For instance, the statistically significant

coefficients on gender in the second models in 1992 and 2000 are a third the size of the estimates

from the first models for each year. Therefore, the table suggests that roughly a third of the

estimated gender gap in those years is due to measurement contamination. Likewise, in 1992,

this contamination biases upward the estimates associated with education, participation, and

radio use. Similar problems arise for the other grouping variables in many years. As with the

bivariate analysis, we find the nuisance dimension affects the regression coefficients and

substantive conclusions in unpredictable ways. Again, the only way to overcome this threat to

validity is to use invariant measures.

Differential Item Functioning

While the six-item scale is sufficiently invariant for many group comparisons, researchers

constructing their own scales are likely to find it valuable to understand which individual items

are most useful—and which are most problematic—for group comparisons. To that end, Figure 4

shows the absolute DIF of each item, averaged across the four years under study.[15] DIF is

typically measured as the difference in the item difficulty based on group membership. These

IRT difficulty estimates are computed from the confirmatory factor analysis coefficients

obtained from a metric invariance model for each year's full scales. The factor loadings are

constrained to be equal across groups but thresholds are group-specific. The first panel of the

figure averages the absolute DIF coefficient values across all grouping variables, while the other

two panels show separately the average DIF for comparisons by gender and education.[16] As

discussed above, the DIF indicates the magnitude of the item bias due to a *group x item*

interaction that remains after partialling out the trait of interest. Thus, larger DIF values indicate

items are more problematic for measuring differences in political knowledge across subgroups

because of the intrusion of nuisance dimensions. Conversely, smaller DIFs indicate the items that may best combine to produce invariant scales.

<<Figure 4 Here>>

A general conclusion from the figure is that many of the items commonly included in knowledge scales are problematic. In particular, open-ended objective knowledge items (shaded black in the figure) demonstrate some of the largest DIF values for every grouping variable. This result is not limited to the Chief Justice and British PM items—those items whose coding schemes were highlighted as most problematic by the ANES administrators (Krosnick et al. 2008)—but rather extends to all the open-ended objective knowledge items. This result provides insight into the debate regarding item format; researchers should avoid these items, instead focusing on multiple choice formats.

Yet, the remaining items are also problematic for many of the grouping variables, with noticeable variation in DIF across groups. For instance, the small DIF values suggest that abortion items are sufficiently useful for knowledge comparisons between genders, but these items exhibit considerable DIF for comparisons between education levels. The services and spending items also demonstrate relatively low DIF values for gender comparisons, reinforcing the results of Dolan (2011) and Stolle and Gidengil (2010) and highlighting the need for researchers to think critically about which items are most relevant for the groups under comparison.

<<Table 4 here>>

Vanishing Tetrad Test

We assume an effects measurement model in the above tests and we therefore must test that assumption using a VTT. To carry out the VTT, a MIMIC model for each year has to be

estimated. We used the two items that represent the highest level of abstraction as the reflective measures and the items measuring objective facts as the causes. As such, we assume objective facts are the basis of schema that provide a more complex context for an abstract understanding of candidate, ideological, and party positions (Axelrod 1973; Conover and Feldman 1984).[17]

To start, we can test whether the formative composite assumption that these subsets of invariant items would constitute an index with no measurement error is supported by the data. We find that the latent variable error terms for the MIMIC models (not shown) are all significant. These results rule out the composite index model as it is inconsistent with the data.

Recall that the cause (MIMIC) model is tetrad nested within the effect model. All the tetrads are expected to vanish in the effect model and none of the tetrads are expected to vanish in the cause model. Because the cause model is nested within the effect model, a significant chi square statistic, based on the discrepancies between what is observed and what is expected, lends support for the cause model as fitting the data better. A non-significant chi square fails to reject the effect model in favor of the cause model.

Table 4 shows that for three survey years, the effect model is the preferred model.[18] All of the nested VTT chi square values, which are the differences between the effect and cause model values (shown at the right of Table 4), are not significant. We conclude from these tests that it is more appropriate to treat the invariant subset of knowledge items as a reflection of the latent variable rather than the cause.

5.   Discussion

Given the centrality of political knowledge, we are surprised by the lack of utility that these measures provide for key questions in the field. The results presented here call into

question a fundamental assumption that underlies a substantial body of research: that combining knowledge items constitutes a measuring device that permits valid group comparisons.

Focusing on the gender analysis, it appears that qualitative differences in how women and men define and pursue political information, coupled with the differential survey response patterns discussed above, present a challenge in the creation of an invariant knowledge scale. Women seem to have different political preferences and priorities than do men (see e.g., Smiley, 1999; Stolle and Gidengil, 2010) and each gender consumes political information in vastly different ways (see e.g., Huckfeldt and Sprague, 1995; Yum and Kendall, 1988). All of these distinctions condition the relevance of particular types of political information. Such differences may impede the construction of invariant knowledge scales because they can cause individual scale items to be differentially linked to gender, as we see here.

Turning to knowledge comparisons for other grouping variables, the results presented here provide six-item subsets for valid comparisons on the basis of education and participation. In addition, these scales also provide possibilities for valid comparisons by income, with the exception for 1996.

We were able to find satisfactory subsets for comparisons on the basis of newspaper use for all years except for 2004. Similarly, comparisons on the basis of TV use (excepting 1996) and radio use appear to be valid using 6-item measures. We note that in contrast to what is observed for other demographic variables, the full scale is invariant in several years for radio and television use. This result leads us to question the causal ordering with regard to the electronic media use variables given what we observe for other demographics. A plausible argument could be made that political knowledge leads to more (or different) media usage, rather than media usage leading to enhanced political knowledge. If media use and political knowledge are the

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joint effects of other factors, such as previous political participation, then the media use variables cannot be the source of item bias in the knowledge scale because they are concurrent or subsequent in the causal chain. This expectation is consistent with our results and suggests an opportunity for future research.

The VTT analysis also provides insight into the relationship between political knowledge as a construct and its associated measures. While the discipline has rarely stated the measurement model explicitly, Deli Carpini and Keeter's (1993; 1996) foundational work on political knowledge measurement uses classical test theory and item response theory to assess validity—implicitly assuming an effect model. Our analysis tests the measurement model and provides empirical support for their assumption and lends guidance to future researchers regarding the appropriate methods for validating political knowledge scales.

This analysis calls attention to an ongoing debate in the field of structural equation modeling regarding the applicability and value of causal and formative measurement models. As scholars in a diverse set of fields have begun to recognize the importance of understanding the link between constructs and their measures, the theory underpinning cause models has received significant attention (e.g., Blalock, 1964; MacCallum and Browne, 1993; Diamantopoulos and Winklhofer, 2001). More recently, some scholars have called the utility of cause models into question (e.g., Bagozzi, 2011; Borsboom, 2006; Iacobucci, 2010). For example, Edwards (2011) argues that causal models rest on the often-untenable assumption that there are no errors in the measurement of formative indicators. Moreover, such models are often difficult or impossible to validate because their estimation requires researchers to make arbitrary decisions that can have important consequences for interpreting the latent construct and, likewise, the construct lacks meaning absent its heterogeneous indicators, preventing tests of construct validity. Further,

Edwards (2001) argues there are philosophical and ontological advantages to conceptualizing measures as effects and taking a critical realist position rather than taking an instrumentalist or operationalist orientation. Classical and modern test theory, along with item response theory, are all based on the latent trait effects model. Among the advantages we would add to his list is the ready availability of an extensive literature of learning theory from cognitive and education psychology to explain the acquisition, retention and activation of knowledge. Political science has utilized this literature for almost half a century in the study of political knowledge (Seeman 1966). Underlying this approach is an assumption of a latent trait that drives item responses as effects that are measured with "tests." In contrast, because cause indicators are exogenous, there is no such theory or explanation of their genesis. Another substantial advantage is that of item selection with an effect model: the application of a domain sampling model.

Domain sampling

Under the domain sampling model, tests are constructed by selecting a number of measures at random from a large homogenous pool of items designed to measure a person's "true score" in a particular domain. (The true score is the person's observed score corrected for measurement error.) A number of different tests could be constructed with other random samples of items from this domain's item pool. The correlation between a given test score and the average of all test scores (the reliability index) can be shown (within sampling error) to equal the square root of the correlation of any test score with another test score (the reliability coefficient). The reliability coefficient is an estimate the ratio of variance in true scores to the variance in observed scores (Nunnally and Bernstein 1994). The important implication of this property is that items (and tests) are interchangeable if they share roughly the same level of reliability and the selection of items covers the difficulty range of the domain under study. Because items are

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interchangeable within a clearly defined domain, the psychometric properties of items are more important than specific item content. In fact, items could be selected at random from among those in the item pool shown to have desirable psychometric properties. But something beyond simple random sampling in selection, such as stratifying the pool of reliable items based on difficulty, would help assure the difficulty range requirement is met, for example. One fundamental desirable psychometric property is measurement invariance across groups.

Other methodological developments allow more precise equating of scores across tests with differing subsets of items as long as there is a common core of items (Kolen and Brennan 2004). So, every item does not have to be asked every survey year for scale scores to be equated with some precision if the requirements outlined above are met.

Conclusion

Our results help explain why researchers have been frustrated in their attempt to measure and explain apparent knowledge gaps between various grouping variables including participation, media use, educational attainment, income, and age. Models seeking to explain observed differences have been unsuccessful because the construct of political knowledge is apparently qualitatively different between subgroups based on these grouping variables—excluding media use. Attempts to explain these differences will thus be unsuccessful, if political knowledge is measured using the full battery, because the measures are not sufficiently invariant to permit valid comparisons. The inconsistent results may also stem from a lack of conceptual clarity regarding the measurement model underpinning political knowledge. Our results suggest that the use of indexes assumed to be measured without error cannot be supported.

The validity of political knowledge scales should not be established by fiat and it is apparent that measurement invariance cannot be ruled out in many instances. Thus, we propose

the following suggestions to maximize the probability of obtaining measurement invariance. First, research employing scales measuring latent traits should demonstrate invariance between the sub-populations of interest. Otherwise, we cannot tell whether differences found between groups on the scale are products of real differences on the trait of interest or products of measurement artifacts. Second, researchers should follow several guidelines that should facilitate the construction of valid scales. Excessively long batteries may inhibit invariance because they increase the opportunity to include items that are related to group membership after controlling for the latent trait. Thus, researchers should limit their scales to the items that are relevant theoretically to each group under study. Likewise, we echo the previous calls for close consideration of the implications of survey response patterns for scale measurement.

Admittedly, these findings and recommendations pose a dilemma for researchers. It is likely that theoretically important items are not sufficiently invariant across subgroups to be included in a scale. Rather than ignore this threat to validity and forge ahead with them anyway, we would suggest that uncovering indicators that are not invariant across groups be considered an important finding in its own right and be used as a catalyst to search for an explanation as to why this is the case.

The good news is that in the context of knowledge scales, a large number of items may not be needed to capture the range of an individual's knowledge. Delli Carpini and Keeter (1993) find that the five best items can explain 75% of the variance in a 39-item measure and the 10 best items account for 90% of the variance[19]. In our analysis, we find the picture is somewhat more complicated in that items that are invariant for some grouping variables are not invariant for others. Thus, survey instruments should increase the variety of knowledge items even as researchers become more selective in their application. Work can also begin on equating items

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using IRT models. We concur with the advice of Smiley (1999) and Stolle and Gidengil (2010) to consider including items gauging respondent's ability to obtain and utilize government benefits and services. This additional variety may improve the utility of knowledge scales by providing scholars with a greater selection of items that are theoretically relevant to the sub-populations of interest.

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[1] We are grateful to an anonymous reviewer for raising this issue.

[2] A notable example of this view is Luskin's (1987) guide to measuring political sophistication. Luskin (1987) treats political sophistication as a conjunction of the size, range, and organization of an individual's political beliefs. Luskin argues that, while these three dimensions of sophistication are related, they each capture a separate—and necessary—dimension. Thus, unlike effect indicators—where the latent variable is determined by the common variance between items (MacKenzie, Podaskoff, and Jarvis 2005) —, these three dimensions (and their associated indicators) each provide a unique source of variance to the underlying construct.

[3] Subscripts for items, individuals, and groups are not shown to simplify the presentation.

[4] Estimation is via mean and variance adjusted weighted least square (WLSMV) and the robust chi-square difference test uses the approach described in Asparouhov and Muthen (2006) based on Satorra and Bentler (1999) and Satorra (2000). See Muthen and Muthen (2010) for additional details.

[5] The cause model in Figure 1B is not identified so estimates cannot be obtained. The MIMIC model is identified by treating at least two of the indicators as effects of the latent variable and the remainder as cause indicators.

[7] For general-ideology and policy-specific placements, the ANES only asks the candidate and party if the respondent is able to place themselves on the relevant scale. Therefore, failure to self-place on any scale necessitates incorrect responses on the candidate and party placements. Similarly, failure to place either candidate results in an incorrect response for the candidate placement and failure to place either party results in an incorrect response for the party placement.

[8] The 2000 ANES uses a five-point scale for the services and spending, defense spending, and jobs and standard of living items for telephone interviews and a seven-point scale for face-to-face interviews. Dow (2009) translates all responses to a five-point scale; we follow his procedure.

[9] In all years, we draw the objective knowledge items from the post-election wave. In 1992 and 1996, we draw all general-ideology and policy-specific placement items from the pre-election wave. In 2000, we draw all policy-specific placement items from the pre-election wave and all general-ideology placement items from the post-election wave. In 2004, we draw all general and policy placement items from the pre-election wave, with the exception of abortion placements which the ANES asked only in the post-election wave.

[10] Treating "don't know" responses as missing follows convention in the literature (see e.g., Delli Carpini and Keeter 1993, Prior 2005, Dow 2009), but, as discussed above, may inflate differences between groups due to differential propensities to guess (Mondak 2001).

[11] This is a likelihood ratio statistic which is distributed as a chi-square variate with degrees of freedom equal to the number of constrained parameters.

[12] Several inconsistencies in the ANES administration of knowledge items from year to year make comparisons between years problematic. Chief among those is the five-point scale that the 2000 study uses on the services and spending, defense spending, and jobs and standard of living items. Due to the reduced number of positions along the scale (five instead of seven), a greater number of ties occur where respondents place the Democratic and Republican candidates (or parties) at the same position on the scale. In such instances, respondents do not receive credit for a correct answer, reducing the mean score for the year. Similarly, the point in the study (pre or post election) that the ANES administered various questions changes from year to year. Thus, campaign effects may create differences in response patterns for such items.

[13] The exceptions are income in 1996, education in 2000, and newspaper use in 2004.

[14] Table 3 omits grouping variables for which the full-scale is invariant.

[15] Table A3 of the appendix provides further information about these estimates.

[16] Figure A1 in the appendix provides the plots for all grouping variables.

[17] It is beyond the scope of this study to review learning theories. But we cite schematic theory as one applicable example that would be familiar to many political scientists. Under this theory, constructive errors are the product of an elaboration process occurring during or shortly after encoding (facts) as general terms are stored as specific instantiations (Alba and Hasher 1983). It is the integration and interpretation of facts that leads to schematic formation and

linkages. The subsequent integration of a greater number of schema leads to more abstract constructions and generalizations and enhance the ability to retrieve the facts underlying the schema. There are other learning theories based on developmental stages that lead to increasing complexity and hierarchical retrieval system models, as well. All of the aforementioned learning theories, however, are based on the idea that synthesis reflects a more complex internal process than the retrieval of a single fact.

[18] For the years 1994-2000, we could utilize effect models for the vanishing tetrad test that specified a correlated error between two effect indicators. The 2004 data, however, require two such correlated error parameters to obtain an acceptable model fit. Unfortunately, that effect model is not tetrad nested within the MIMIC model and prevents it application of the VTT. The effect model is preferred over the causal indicator MIMIC model in the three years that we could test.

[19] The five-item subset that Delli Carprini and Keeter (1993) recommend are from the 1991 ANES Pilot Study and several of those items are not repeated in the survey years under study here. This analysis is based on a more recently utilized knowledge scale in Dow (2009).

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Table 1. Point-biserial correlations between knowledge scales and participation indicators.

	1992		1996		2000		2004	
	Full scale	Six-item	Full scale	Six-item	Full scale	Six-item	Full scale	Six-item
Did R report voting?	.37	.34	.36	.31	.37	.35	.41	.39
Did R try to persuade anyone to vote for or against a candidate?	.13	.13	.27	.25	.24	.24	.25	.26
Did R wear a campaign button, etc.?	.16	.14	.13	.14	.17	.17	.19	.18
Did R go to any political meetings, etc.?	.14	.14	.14	.12	.14	.14	.13	.13
Did R do any work for one of the candidates?	.08	.08	.12	.11	.08	.07	.11	.10
Did R give money to an individual candidate?	.18	.18	.15	.16	.19	.19	.24	.22
Did R give money to a political party?	.14	.13	.16	.16	.18	.15	.21	.22
Did R give money to any other political group?	.20	.21	.19	.17	.16	.17	.19	.18

Table 2. How measurement non-invariance influences bivariate effect sizes.

	Non-Invarient Full scale	Invarient 6-item	Effect size inflation
	Cohen's d		
2004			
Gender	.32	.58	-84%
Income	.58	.52	11%
Participation	.56	.57	-2%
Education	.94	.90	4%
Age	.06	.18	-175%
2000			
Gender	.55	.48	13%
Income	.74	.65	12%
Participation	.61	.60	2%
1996			
Gender	.35	.39	-13%
Education	.95	.85	10%
1992			
Gender	.45	.39	13%
Income	.66	.60	8%
Participation	.61	.59	4%
Education	1.16	1.10	5%

Note: The effect size inflation measures the extent to which the non-invariant full scales inflate (or deflate) the effect size as measured by the invariant six-item scales. Aside from media use indicators (not shown here), the full scale is not invariant for any grouping variables except participation in 1996. The six-item scales are invariant for all grouping variables except income in 1996, education in 2000, and age in 1992-2000

Table 3. OLS regressions of full scale on grouping variables and invariant 6-item scales.

	1992			1996			2000			2004	
	Model 1	Model 2		Model 1	Model 2		Model 1	Model 2		Model 1	Model 2
Six-item scale		0.81*			0.83*			0.87*			0.97*
		(0.012)			(0.013)			(0.014)			(0.019)
College Degree	0.18*	0.02*		0.18*	0.04*					0.15*	0.01
	(0.016)	(0.007)		(0.015)	(0.007)					(0.020)	(0.009)
Gender	-0.06*	-0.02*		-0.03	0.01		-0.06*	-0.02*		-0.04*	0.01
	(0.014)	(0.006)		(0.014)	(0.006)		(0.017)	(0.007)		(0.018)	(0.008)
Income	0.05*	0.01					0.11*	0.02*		0.03	0.02*
	(0.015)	(0.007)					(0.017)	(0.008)		(0.019)	(0.008)
Newspaper use	0.10*	0.01		0.08*	0.02*		0.10*	0.01		0.07*	0.00
	(0.015)	(0.007)		(0.015)	(0.007)		(0.018)	(0.008)		(0.020)	(0.009)
Participation	0.09*	0.02*		0.07*	0.01		0.09*	0.01		0.06*	0.01
	(0.014)	(0.006)		(0.015)	(0.007)		(0.017)	(0.007)		(0.018)	(0.008)
Radio use	0.06*	0.01*		0.07*	0.01		0.12*	0.01		0.08*	0.02*
	(0.014)	(0.006)		(0.015)	(0.007)		(0.017)	(0.008)		(0.018)	(0.008)
TV use	0.05	0.00					0.05*	0.00		0.07*	-0.01
	(0.024)	(0.011)					(0.023)	(0.010)		(0.028)	(0.012)
TV frequency				0.01	0.00		0.04*	0.01		0.01	-0.01
				(0.015)	(0.006)		(0.017)	(0.007)		(0.019)	(0.008)
Age										0.00	-0.02*
										(0.018)	(0.008)
Intercept	0.38*	0.17*		0.50*	0.13*		0.28	0.11*		0.46*	0.05*
	(0.026)	(0.012)		(0.017)	(0.010)		(0.025)	(0.011)		(0.031)	(0.016)
N	1028	1028		973	973		886	886		621	621
R^2	0.35	0.87		0.25	0.85		0.28	0.86		0.28	0.86

Note: * $p < .05$. OLS regression. Standard errors in parentheses. Table omits grouping variables for which the full-scale is invariant. Model 2 coefficients indicate the magnitude and direction of the biases in effect sizes introduced by the non-invariant scales.

Table 4. Vanishing Tetrad Test (VTT) Chi Square values for 1992-2000[a].

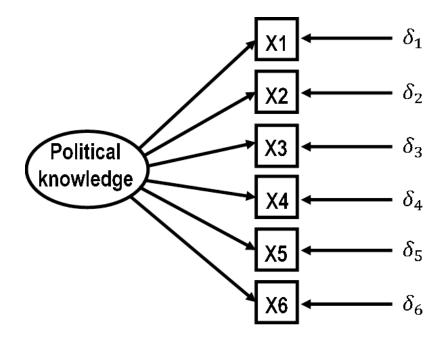|	Effect Model χ^2	DF	MIMIC Model χ^2	DF	VTT χ^2	DF	p-value
1992	6.1	8	1.6	3	4.5	5	.48
1996	8.8	8	.4	2	8.4	6	.21
2000	9.4	7	6.4	3	2.9	4	.57

Note: A statistically significant VTT χ^2 indicates that the cause model best fits the data. A non-significant χ^2 fails to reject the effect model in favor of the cause model.

[a] The best fitting models for 2004 were not tetrad nested so the VTT could not be carried out for that year.

Figure 1. Effect and Cause Measurement Models.

Panel A. Six-item reflective effect model.
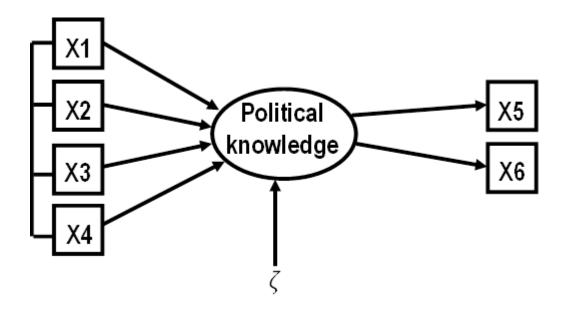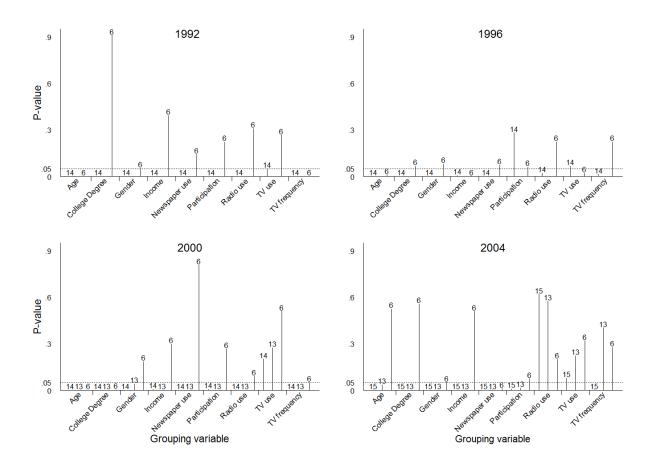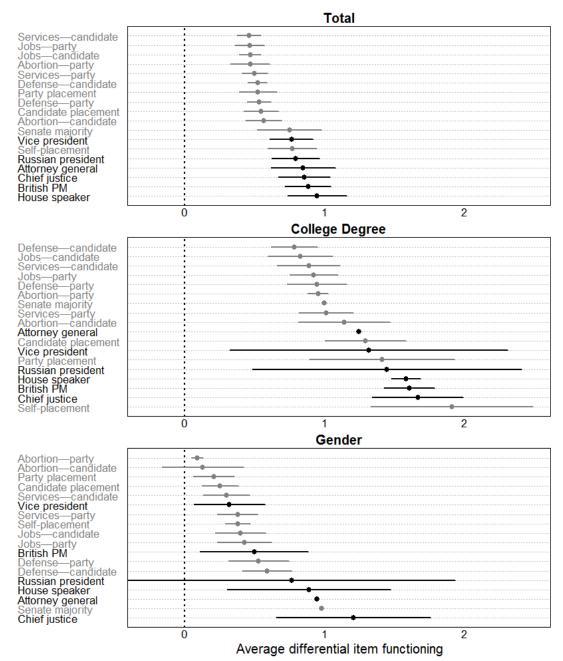

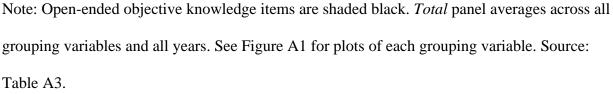
Panel B. Six-item cause model.

Figure 2. Multiple Indicator Multiple Causes Model (MIMIC).

Figure 3. p-values associated with χ2 test of change in model fit when the two sets of measurement parameters are constrained to be equal across groups.

Note: Scales with p-values > .05 are said to be invariant with respect to the associated grouping variable, while scales falling below this threshold are non-invariant. Numbered points indicate the number of items included in each scale. The full scales includes 14 items in 1992-2000 and 15 items in 2004. The new scales includes 6 items in all years. The 13 item scales in 2000-2004 remove from the full scale items with administration problems documented by the ANES (Krosnick, Lupia, DeBell, and Donakowski, 2008). Source: Table A2.

Figure 4. Average differential item functioning for selected grouping variables, 1992-2004.

Note: Open-ended objective knowledge items are shaded black. *Total* panel averages across all grouping variables and all years. See Figure A1 for plots of each grouping variable. Source: Table A3.

7. Appendix

Table A1. ANES items used to create political knowledge scale: 1992-2004. (Adapted from Dow 2009).

		1992	1996	2000	2004
Ideological	Self-placement	X	X	X	X
	Candidate placement	X*	X*	X*	X*
	Party placement	X	X	X	X
Objective knowledge	Vice president	X	X		X*
	Chief justice supreme court	X*	X*	X	X
	Russian President	X	X*		
	British PM			X*	X
	House of representatives speaker	X*	X		X*
	Senate majority leader			X*	
	Attorney general			X	
Issue placement	Services and spending—candidate	X*	X*	X*	X
	Services and spending—party	X	X	X	X*
	Defense spending—candidate	X	X*	X*	X*
	Defense spending—party	X*	X	X	X
	Jobs and Std of living—candidate	X	X*	X	X
	Jobs and Std of living—party	X		X	X
	Abortion—candidate	X*	X	X*	X*
	Abortion—party		X		X

* Used for six-item scale

Table A2. Model fit statistics for invariance tests.

Group Comparison	Year	Scale Items	Invariance Test $\chi 2$	df
Age	2004	15	32.5*	13
0 = below median	2004	6	3.2	4
1 = at or above median	2000	14	48.4*	12
	2000	6	27.8*	4
	1996	14	34.4*	12
	1996	6	13.1*	4
	1992	14	69.7*	12
	1992	6	18.0*	4
College Degree	2004	15	46.2*	13
0 = no degree	2004	6	3	4
1 = degree	2000	14	48.6*	12
	2000	6	15.4*	4
	1996	14	36.8*	12
	1996	6	8.8	4
	1992	14	49.7*	12
	1992	6	1	4
Gender	2004	15	66.3*	28
0 = male	2004	6	9.4	4
1 = female	2000	14	80.1*	26
	2000	6	6.2	4
	1996	14	91.3*	26
	1996	6	8.3	4
	1992	14	75.9*	26
	1992	6	9.4	4
Income	2004	15	50.8*	13
0 = below median	2004	6	3.3	4
1 = at or above median	2000	14	27.2*	12
	2000	6	4.9	4
	1996	14	27.2*	12
	1996	6	17.4*	4
	1992	14	45.8*	12
	1992	6	4.1	4
Newspaper use	2004	15	35.1*	13
0 = Did not read news about the campaigns	2004	6	13.0*	4
1 = Did read	2000	14	34.6*	12

	2000	6	1.6	4
	1996	14	42.8*	12
	1996	6	8.6	4
	1992	14	47.5*	12
	1992	6	6.9	4
Participation	2004	15	27.9*	13
0 = did not participate	2004	6	8.5	4
1 = participated in 1 or more campaign activities	2000	14	27.5*	12
	2000	6	5.2	4
	1996	14	14.3	12
	1996	6	9	4
	1992	14	45.3*	12
	1992	6	5.7	4
Radio use	2004	15	10.9	13
0 = Did not listen to news about the campaigns	2004	6	6	4
1 = Did listen	2000	14	31.3*	12
	2000	6	8	4
	1996	14	23.9*	12
	1996	6	5.7	4
	1992	14	32.1*	12
	1992	6	4.8	4
TV use	2004	15	20.7	13
0 = Did not watch news about the campaigns	2004	6	4.7	4
1 = Did watch	2000	14	15.8	12
	2000	6	3.3	4
	1996	14	20	12
	1996	6	11.5*	4
	1992	14	21	12
	1992	6	5.2	4
TV frequency	2004	15	32.9*	13
0 = below median	2004	6	5.1	4
1 = at or above median	2000	14	32.1*	12
	2000	6	9.5*	4
	1996	14	25.3*	12
	1996	6	5.7	4
	1992	14	42.3*	12
	1992	6	23.9*	4

* p < .05. Scales with p-values > .05 are said to be invariant with respect to the associated grouping variable, while scales falling below this threshold are non-invariant.

Table A3. Average differential item functioning by grouping variable, 1992-2004.

Variable	Group	Mean	N	Std. Deviation	Std. Error of Mean
Total	Age	0.21	57	0.19	0.026
	College Degree	1.21	57	0.40	0.053
	Gender	0.47	57	0.33	0.044
	Income	0.73	57	0.27	0.035
	Newspaper use	0.77	57	0.40	0.053
	Participation	0.65	57	0.17	0.023
	Radio use	0.67	57	0.20	0.026
	TV frequency	0.27	57	0.21	0.028
	TV use	0.59	57	0.22	0.029
	Total	0.62	513	0.39	0.017
Abortion—candidate	Age	0.11	4	0.09	0.043
	College Degree	1.14	4	0.24	0.118
	Gender	0.13	4	0.21	0.105
	Income	0.52	4	0.23	0.117
	Newspaper use	0.78	4	0.27	0.137
	Participation	0.77	4	0.19	0.097
	Radio use	0.64	4	0.22	0.108
	TV frequency	0.30	4	0.21	0.105
	TV use	0.69	4	0.34	0.172
	Total	0.56	36	0.38	0.064
Abortion—party	Age	0.27	2	0.11	0.077
	College Degree	0.95	2	0.02	0.017
	Gender	0.09	2	0.01	0.010
	Income	0.48	2	0.10	0.069
	Newspaper use	0.52	2	0.19	0.138
	Participation	0.65	2	0.14	0.101
	Radio use	0.62	2	0.18	0.125
	TV frequency	0.13	2	0.03	0.021
	TV use	0.50	2	0.26	0.183
	Total	0.47	18	0.28	0.066
Attorney general	Age	0.33	1	.	.
	College Degree	1.24	1	.	.
	Gender	0.94	1	.	.
	Income	1.26	1	.	.

	Newspaper use	0.97	1	.	.
	Participation	0.81	1	.	.
	Radio use	0.83	1	.	.
	TV frequency	0.65	1	.	.
	TV use	0.56	1	.	.
	Total	0.84	9	0.31	0.102
British PM	Age	0.58	2	0.24	0.173
	College Degree	1.60	2	0.06	0.042
	Gender	0.49	2	0.13	0.090
	Income	1.04	2	0.03	0.020
	Newspaper use	1.05	2	0.13	0.093
	Participation	0.78	2	0.02	0.017
	Radio use	0.85	2	0.21	0.148
	TV frequency	0.75	2	0.01	0.008
	TV use	0.78	2	0.14	0.103
	Total	0.88	18	0.33	0.078
Candidate placement	Age	0.10	4	0.09	0.043
	College Degree	1.29	4	0.21	0.104
	Gender	0.25	4	0.09	0.047
	Income	0.63	4	0.14	0.070
	Newspaper use	0.57	4	0.14	0.070
	Participation	0.69	4	0.08	0.039
	Radio use	0.65	4	0.22	0.109
	TV frequency	0.19	4	0.12	0.061
	TV use	0.54	4	0.16	0.081
	Total	0.54	36	0.36	0.061
Chief justice	Age	0.29	4	0.32	0.158
	College Degree	1.67	4	0.23	0.117
	Gender	1.20	4	0.40	0.198
	Income	1.26	4	0.30	0.151
	Newspaper use	1.24	4	0.35	0.177
	Participation	0.62	4	0.23	0.114
	Radio use	0.79	4	0.18	0.089
	TV frequency	0.16	4	0.11	0.057
	TV use	0.46	4	0.33	0.167
	Total	0.85	36	0.55	0.092
Defense—candidate	Age	0.22	4	0.13	0.063
	College Degree	0.78	4	0.12	0.060

	Gender	0.59	4	0.13	0.064
	Income	0.59	4	0.07	0.034
	Newspaper use	0.49	4	0.12	0.060
	Participation	0.58	4	0.11	0.054
	Radio use	0.62	4	0.17	0.087
	TV frequency	0.27	4	0.19	0.093
	TV use	0.54	4	0.13	0.065
	Total	0.52	36	0.20	0.034
Defense—party	Age	0.22	4	0.09	0.045
	College Degree	0.94	4	0.15	0.077
	Gender	0.53	4	0.15	0.077
	Income	0.66	4	0.22	0.109
	Newspaper use	0.55	4	0.08	0.040
	Participation	0.61	4	0.13	0.066
	Radio use	0.60	4	0.12	0.061
	TV frequency	0.19	4	0.14	0.072
	TV use	0.49	4	0.08	0.041
	Total	0.53	36	0.25	0.041
House speaker	Age	0.53	3	0.43	0.248
	College Degree	1.58	3	0.06	0.033
	Gender	0.89	3	0.32	0.183
	Income	1.02	3	0.15	0.085
	Newspaper use	1.88	3	0.62	0.360
	Participation	0.66	3	0.21	0.123
	Radio use	0.72	3	0.06	0.034
	TV frequency	0.36	3	0.14	0.078
	TV use	0.87	3	0.13	0.077
	Total	0.95	27	0.53	0.103
Jobs—candidate	Age	0.14	4	0.12	0.061
	College Degree	0.82	4	0.17	0.083
	Gender	0.40	4	0.13	0.065
	Income	0.54	4	0.12	0.062
	Newspaper use	0.51	4	0.13	0.065
	Participation	0.62	4	0.18	0.092
	Radio use	0.54	4	0.10	0.048
	TV frequency	0.18	4	0.11	0.057
	TV use	0.46	4	0.07	0.035
	Total	0.47	36	0.23	0.039

Jobs—party	Age	0.08	3	0.07	0.039
	College Degree	0.92	3	0.09	0.055
	Gender	0.43	3	0.11	0.062
	Income	0.63	3	0.07	0.041
	Newspaper use	0.49	3	0.15	0.086
	Participation	0.52	3	0.03	0.017
	Radio use	0.61	3	0.18	0.105
	TV frequency	0.11	3	0.13	0.074
	TV use	0.40	3	0.05	0.028
	Total	0.47	27	0.26	0.051
Party placement	Age	0.09	4	0.08	0.038
	College Degree	1.41	4	0.37	0.186
	Gender	0.21	4	0.11	0.053
	Income	0.62	4	0.15	0.076
	Newspaper use	0.50	4	0.11	0.057
	Participation	0.49	4	0.13	0.063
	Radio use	0.63	4	0.23	0.114
	TV frequency	0.23	4	0.15	0.074
	TV use	0.53	4	0.06	0.028
	Total	0.52	36	0.40	0.066
Russian president	Age	0.38	2	0.13	0.092
	College Degree	1.44	2	0.32	0.224
	Gender	0.76	2	0.38	0.272
	Income	0.92	2	0.00	0.002
	Newspaper use	1.00	2	0.34	0.244
	Participation	0.63	2	0.10	0.071
	Radio use	0.74	2	0.04	0.032
	TV frequency	0.44	2	0.08	0.060
	TV use	0.82	2	0.06	0.044
	Total	0.79	18	0.35	0.081
Self-placement	Age	0.18	4	0.05	0.025
	College Degree	1.91	4	0.42	0.209
	Gender	0.38	4	0.07	0.033
	Income	0.90	4	0.10	0.052
	Newspaper use	0.79	4	0.18	0.092
	Participation	0.83	4	0.22	0.111
	Radio use	0.94	4	0.34	0.170
	TV frequency	0.32	4	0.22	0.108

	TV use	0.68	4	0.07	0.036
	Total	0.77	36	0.52	0.087
Senate majority	Age	0.22	1	.	.
	College Degree	1.00	1	.	.
	Gender	0.98	1	.	.
	Income	0.72	1	.	.
	Newspaper use	1.10	1	.	.
	Participation	0.84	1	.	.
	Radio use	0.89	1	.	.
	TV frequency	0.30	1	.	.
	TV use	0.67	1	.	.
	Total	0.75	9	0.31	0.102
Services—candidate	Age	0.10	4	0.06	0.029
	College Degree	0.88	4	0.16	0.081
	Gender	0.30	4	0.12	0.060
	Income	0.55	4	0.09	0.046
	Newspaper use	0.59	4	0.11	0.055
	Participation	0.51	4	0.14	0.069
	Radio use	0.58	4	0.16	0.078
	TV frequency	0.15	4	0.12	0.058
	TV use	0.46	4	0.07	0.033
	Total	0.46	36	0.25	0.042
Services—party	Age	0.12	4	0.10	0.049
	College Degree	1.01	4	0.14	0.070
	Gender	0.38	4	0.10	0.052
	Income	0.66	4	0.05	0.025
	Newspaper use	0.59	4	0.16	0.079
	Participation	0.52	4	0.11	0.053
	Radio use	0.54	4	0.20	0.102
	TV frequency	0.18	4	0.11	0.053
	TV use	0.50	4	0.08	0.041
	Total	0.50	36	0.27	0.046
Vice president	Age	0.36	3	0.18	0.105
	College Degree	1.31	3	0.54	0.312
	Gender	0.32	3	0.14	0.080
	Income	0.78	3	0.34	0.198
	Newspaper use	0.97	3	0.07	0.038
	Participation	0.85	3	0.20	0.115

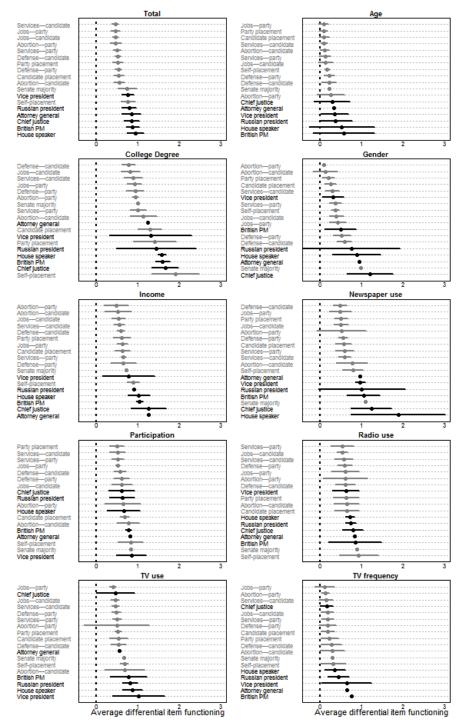|				
Radio use	0.62	3	0.18	0.104
TV frequency	0.64	3	0.33	0.188
TV use	1.01	3	0.34	0.198
Total	0.76	27	0.39	0.075

Figure A1. Average differential item functioning by grouping variable, 1992-2004.

Note: Open-ended objective knowledge items are shaded black. *Total* panel averages across all grouping variables and all years. Source: Table A3.