On Modeling the Psychological Foundations of Support for Donald Trump

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Scholars have identified many psychological factors correlated with support for Donald Trump; however, attempts at modeling Trump support tend to suffer from omitted variable bias on the one hand, or multicollinearity on the other. Both issues obscure inferences. Using two nationally-representative surveys, we demonstrate the perils of including or failing to include many of these factors in models of Trump support. We then reconceptualize the psychological sources of Trump support as components of a broader "profile" of factors that explains Trump support in 2018 and vote choice in 2016, as well as attitudes about issues connected to Trump. Moreover, this profile – an amalgamation of attitudes about, for example, racial groups, immigrants, and political correctness – outperforms partisanship and ideology as predictors of Trump support and is negatively related to support for mainstream Republican candidates. Our analyses suggest that Trump benefitted from activating dimensions of public opinion that transcend traditional party cleavages.

Keywords: Donald Trump, elections, vote choice, partisanship, racial prejudice

Word Count: 7,474

Why do Americans support Donald Trump? Trump's status as a non-traditional, inexperienced outsider has made the answer to this question considerably more elusive than similar questions asked about previous presidents. Even intra-party dynamics appear to be different, with many researchers embracing the idea that Trump supporters differ from non-Trump supporting Republicans in important ways (Reny, Collingwood and Valenzuela 2019, Barber and Pope 2019, Blum and Parker 2019). The idiosyncrasies of Trump's ascent, amidst an increasingly polarized and sorted political culture, has elevated the accounting of Trump support to a "key social-science challenge" (Federico and de Zavala 2018, 110).

What explanations does the literature offer? On the one hand, classical social-psychological antecedents of political behavior – partisan and ideological identities – are consistently strong predictors of Trump support (i.e., positive feelings toward him and vote choice) (Bartels 2018). On the other hand, an expanding literature has uncovered many other deep-seated social-psychological antecedents of Trump support that display predictive power despite controls for partisanship and ideology (Grossmann 2019). These social-psychological factors range from group orientations, such as racial prejudice and sexism, to more general postures toward political power and culture, such as anti-political correctness attitudes and conspiracy thinking (e.g., Schaffner, Macwilliams and Nteta 2018). While any one of these factors is unlikely to supplant the role of partisan and ideological orientations on its own, they may still contribute to a more complete theoretical and empirical accounting of Trump support, as others have demonstrated.

Even though researchers now have a better grasp of which social-psychological orientations might lead to support for Trump (either having positive feelings towards him or preferring him over other candidates), this literature has developed in a rather piecemeal fashion,

leaving questions about how to best model Trump support. This can partially be attributed to Trump's tactics catching researchers off guard and without the necessary survey instruments to test explanations against one another. Consequently, many studies fail to include potentially confounding explanations of Trump support, leading to omitted variable bias. Yet, other studies find that inclusion of appropriate controls can result in unstable estimates of the effects of key social-psychological predictors (e.g., Grossman and Thaler 2018), due to multicollinearity. Regardless of the statistical problem, our understanding of the psychological antecedents of Trump support are being obscured. Ultimately, while our understanding of the various factors associated with Trump support has broadened to include many explanations, it has not yet sharpened to the point of generating a "best" model of Trump support.

In this study, we use unique data from the 2018 Cooperative Congressional Election Study (CCES) and publicly available data from the 2016 American National Election Study (ANES) to demonstrate these problems. After observing high correlations between constructs such as racial resentment, sexism, and xenophobia, we demonstrate the perils of either including the many hypothesized predictors of Trump support in a single model, or of failing to include many of such predictors. To address this double-edged sword, we model Trump support using a constellation of attitudes and orientations about groups and political culture – a "profile." The Trump profile we construct either matches or outperforms partisanship and ideology in predicting Trump vote choice, general support for Trump, and a host of attitudes about several of Trump's core issues (e.g., building the U.S.–Mexico border wall). Importantly, we find that this profile does not merely capture partisanship or ideology in another way; indeed, it is negatively correlated with support for establishment Republicans running in the 2016 primaries.

Our findings have several theoretical and methodological implications for the study of vote choice among a socially sorted and politically polarized electorate. First, given that psychological orientations toward social, racial, and political "others" are, as the burgeoning literature on social identity suggests (e.g., Mason 2018), frequently related to each other, perhaps such orientations should not be treated separately. Our analyses empirically demonstrate the inferential pitfalls of separately modeling constructs that have become tightly interwoven over time. Second, whereas scholars of American politics have typically focused on voters' responses to mainstream party appeals, we produce supportive evidence that other powerful dimensions of opinion exist outside of traditional conceptualizations of left-right politics, which – when activated by strategic politicians – can win elections, upend party agendas, and produce reactionary politics. We further discuss these implications and more in the conclusion.

The Many Predictors of Support for Donald Trump

Since 2015, scholars across social scientific disciplines have attempted to explain why some Americans throw their support behind Donald Trump. Traditional explanations, such as partisanship (Republicanism) and ideology (conservatism), both account for considerable variance in attitudes toward Trump compared to Clinton, just as they have for most electoral contests since the advent of modern polling (Bartels 2018). Even so, these factors cannot explain why some key, historically Democratic districts turned out for Trump, nor can they account for intra-party differences in support for Trump versus his Republican competitors. A complete accounting of the sources of Trump's support requires more than the traditional model of vote choice has to offer. In attempting to decipher precisely what additional factors may play a role in Trump support, researchers have, for the most part, started with Trump's behaviors and

communications and made inferences about which elements of these things might resonate with the mass public. This interdisciplinary exercise has resulted in many plausible explanations for Trump support, spanning the sociodemographic, psychological, and cultural.

For the most part, examinations of sociodemographic explanations have garnered only weak support. Education, for example, is negatively associated with Trump support, but it is unclear whether something about a lack of educational attainment itself makes Trump more appealing or lower educational attainment merely serves as a proxy for other orientations (Silver 2016). Others saw a theme of working class vulnerability in Trump's campaign communications (Bucci 2017, Morgan and Lee 2018), but a wide range of analyses employing different models, data, and assumptions suggest that – at best – economics is an inconsistent predictor of support (e.g., Silver 2016, Mutz 2018, Ogorzalek, Piston and Puig 2019, Green and McElwee 2018).

Of course, it is easy to find examples of racism, sexism, xenophobia, conspiracism, and authoritarianism in Trump's rhetoric on and off the campaign trail (e.g., Finley and Esposito 2019, Oliver and Rahn 2016, Jamieson and Taussig 2017, Sanchez 2018). Thus far, these social-psychological orientations have been fruitful avenues for exploring Trump support. Many researchers have found a connection between racial orientations – from white identity to racial prejudice – and Trump support (Green and McElwee 2018, Schaffner, et al. 2018, Engelhardt 2019, Abramowitz and McCoy 2019, Lajevardi and Oskooii 2018, Donovan and Redlawsk 2018, Craig, Rucker and Richeson 2018, Sides, Tesler and Vavreck 2019, Jardina 2019, Lopez Bunyasi 2019). Immigration being a key element of Trump's platform, xenophobic tendencies among some members of the mass public also seems to correlate with Trump support (Manza and Crowley 2018, Hooghe and Dassonneville 2018, Wright and Esses 2019). The same can be said about attitudes toward women, from hostile to ambivalent sexism (Bracic, Israel-Trummel and

Shortle 2019, Frasure-Yokley 2018, Schaffner, et al. 2018, Setzler and Yanus 2018, Cassese and Holman 2019, Deckman and Cassese 2019). Importantly, attitudes about racial groups, immigration, and gender each played a greater role in explaining vote choice in 2016 than in previous elections, suggesting that Trump activated these orientations in a way that previous Republican presidential candidates had not (Sides, Tesler and Vavreck 2017, Donovan and Redlawsk 2018, Reny, et al. 2019, Valentino, Wayne and Oceno 2018).

Finally, several broad orientations toward political power and culture can be found among both Trump's rhetoric and the psychology of his supporters. Negative attitudes toward political correctness – a posture regarding "appropriate" interactions with members of various groups – are correlated with Trump support (Conway, Repke and Houck 2017). Trump is also famous for his engagement with populist and conspiratorial ideas (Oliver and Rahn 2016), garnering him labels such as "conspiracy theorist in chief" (Cillizza 2017). Indeed, both populist (Carmines, Ensley and Wagner 2016) and conspiratorial (Cassino 2016) views are positively related to support for Trump. Finally, Trump's "strong-man" image elevated authoritarian views in comparison to previous elections (Knuckey and Hassan 2019), all but ensuring that various conceptualizations of authoritarianism are associated with Trump support (Womick, et al. 2018, Ludeke, Klitgaard and Vitriol 2018, MacWilliams 2016).

Taking stock of these factors and how they relate to both each other and Trump support, we can observe that while our understanding of the antecedents of Trump support has broadened, it has not sharpened in terms of actually producing a general model of Trump support. While this eclectic literature points to many potential causes of Trump support, it is still unclear what the "best" explanations of Trump support are, and therefore what a good empirical model of Trump support should look like. To compound this deficiency, it is evident from the literature that many

of the social-psychological factors hypothesized to explain Trump support are highly correlated. Indeed, Grossmann and Thaler (2018, 768-770) find that as models are altered to include or exclude particular explanatory factors (e.g., racial resentment), estimates associated with other explanatory factors subsequently change quite radically. For example, while several studies find that authoritarianism is a significant predictor of Trump support (e.g, MacWilliams 2016), Grossmann and Thaler (2018) find that the inclusion of controls for other attitudinal variables results in a non-statistically significant coefficient estimate for authoritarianism. This should not be taken as an indication that authoritarianism is not an important predictor of Trump support, but rather, as Grossman and Thaler (2018, 768) suggest, that some attitudinal factors theoretically and empirically overlap, share tendencies that are "rooted" in each other.

We therefore contend that it is more efficient to conceptualize the explanatory factors explored above as elements of a broader profile of orientations, rather than as individual attitudinal explanations to be tested against each other or simply controlled for. This reconceptualization of the sources of Trump support will, as we demonstrate, ameliorate the problems associated with omitted variable bias and multicollinearity. It will also provide the bedrock of more unified theory of the sources of Trump support – one built not on any one explanation, but a constellation of attitudes and orientations toward salient political groups and a changing political culture.

Data and Analytical Strategy

In order to simultaneously examine the effects of the many factors posited to explain support for Donald Trump, we require measures of most of these factors on a single survey. Therefore, we fielded a unique module of items on the 2018 CCES that included indicators to

estimate attitudes regarding racial minorities, women, immigrants, political correctness, and conspiracy thinking (see Table 1). The survey was administered to 1,000 respondents during October 2018 and is intended to capture the factors driving support for Trump two years into his term. That said, we subsequently employ the 2016 ANES, which included similar survey instruments, with two particular goals in mind: 1) to test the power of our analytical strategy in a different temporal context, and 2) to examine the effects of the Trump support factors on support for other Republican candidates in the 2016 Republican primaries.

Table 1: Question wording for all items employed below, 2018 CCES.

Racial Resentment

1) Generations of slavery and discrimination have created conditions that make it difficult for blacks to work their way out of the lower class.
2) It's really a matter of some people not trying hard enough; if blacks would only try harder they could be just as well off as whites.
3) Over the past few years, blacks have gotten less than they deserve.
4) Irish, Italian, Jewish, and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors.

Sexism

1) Women should earn the same wages as their male counterpart.
2) A woman's place is in the home.
3) The news media have been showing more concern about the treatment of women than is warranted by women's actual experiences.
4) Feminists are making entirely reasonable demands of men.

Anti-Immigrant Attitudes

1) Illegal immigrants increase crime in the US.
2) Illegal immigrants decrease wages for Americans.
3) Immigrants contribute more in taxes than they receive in health and welfare services.
4) Immigration in general should be slowed down.

Anti-PC Attitudes

1) People can't say what they think about important topics, because of political correctness.
2) Political correctness has gone too far.
3) Too many people are easily offended these days over other people's language.

Conspiracy Thinking

1) Much of our lives are being controlled by plots hatched in secret places.
2) Even though we live in a democracy, a few people will always run things anyway.
3) The people who really "run" the country are not known to the voters.
4) Big events like wars, the current recession, and the outcomes of elections are controlled by small groups of people who are working in secret against the rest of us

Our analytical strategy unfolds in four steps. First, we employ the CCES data to examine the interrelation between the Trump support factors, with an emphasis on the stability of observed effects across model specifications. Here, we are interested in understanding the extent to which inferences about the effect of any given predictor of Trump support are contingent on the inclusion or exclusion of other variables in the model. Second, we present a strategy for conceptualizing and measuring the Trump support factors which results in an empirical estimate of a "Trump profile" – or, amalgamation of attitudes associated with Trump support. Third, we demonstrate that this profile is a better predictor of Trump support and attitudes associated with Trump than any individual factor alone, all factors separately applied, or partisanship and ideology. Finally, we estimate the Trump profile using a close approximation of variables from the 2016 ANES, confirming the robustness of previous findings and showcasing the ability of the profile to discriminate between support for Trump and support for other Republican candidates.

Empirical Analysis

Each of the factors posited to explain Trump support, excepting partisanship and ideology, are measured via multiple-item scales. This allows us to reduce measurement error and employ sharper estimates. This also means that when we compare the effects of these variables, differences are less likely to be due to measurement error, but to true differences in the (controlled) effect of these variables, assuming that the empirical models we have specified are reasonably correct. Information about the number of items composing each scale, statistical reliability, and the proportion of shared inter-item variance accounted for by the first factor of an exploratory factor analysis appear in Table 2. Each of the scales is statistically reliable (i.e., high alpha) and squarely unidimensional (i.e., high proportion of variance explained by first factor).

Thus, these variables will be on a roughly equal playing field in terms of the influence of measurement error when comparing their effects in models below (Westfall and Yarkoni 2016).[1]

Table 2: Characteristics and psychometric properties of Trump support variable scales.

	# of Items	Cronbach's Alpha	Prop. Variance Explained
Racial Resentment	4	0.908	0.930
Sexism	4	0.685	0.842
Anti-Immigrant Attitudes	4	0.847	0.957
Anti-PC Attitudes	3	0.861	0.992
Conspiracy Thinking	4	0.774	0.896

We begin our investigation by examining the simple bivariate relationships between the hypothesized predictors. Table 3 contains correlations between each pair of factors, as well as partisanship and ideology. Most of the correlations are quite large and statistically significant at the $p < 0.05$ level. The exception is conspiracy thinking, which – consistent with previous studies (Uscinski, Klofstad and Atkinson 2016, Miller 2020) – appears less strongly related to the other variables. Racial resentment, sexism, anti-immigrant attitudes, anti-PC attitudes, and traditional political orientations are all highly correlated, with correlations ranging from 0.489 to 0.725.

From the magnitude of the intercorrelations in Table 3, one can already imagine potential difficulties in disentangling the effects of each of these constructs on support for Trump.

[1] The sexism scale is slightly below the 0.70 cutoff for alpha that researchers tend to employ. We are not, however, particularly concerned about this. First, the alpha reliability estimate is only lower than the 0.70 cutoff by 0.015. Second, this cutoff is largely arbitrary. Finally, other measures of reliability that perform better than Cronbach's alpha, such as the greatest split half reliability or the greatest lower bound, exceed 0.70.

Multicollinearity may affect substantive inferences by increasing standard errors, leading to inaccurate tests of statistical significance. It can also increase the sensitivity of estimates to model specification (Winship and Western 2016). Relatedly, omitting variables – especially ones that are highly related to others in the model – causes issues of a different sort. Models omitting too many variables will be mis-specified and incapable of adjudicating between the various explanations for Trump support. Further, omitting variables that are highly correlated with others included in the model may produce biased estimates, and the likelihood of such a scenario increases as the magnitude of the intercorrelations between predictors increases.

Table 3: Correlations between hypothesized predictors of Trump support. Pearson correlation coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Racial Resentment	1.000					
(2) Sexism	0.634*	1.000				
(3) Anti-Immigrant Attitudes	0.725*	0.596*	1.000			
(4) Anti-PC Attitudes	0.634*	0.514*	0.634*	1.000		
(5) Conspiracy Thinking	0.108*	0.138*	0.145*	0.214*	1.000	
(6) Partisanship	0.579*	0.531*	0.586*	0.489*	0.029	1.000
(7) Ideological Self-identification	0.642*	0.612*	0.662*	0.565*	0.072	0.680*

Cell entries are Pearson correlation coefficients.

* denotes $p < 0.05$ level with respect to a two-tailed test.

To determine a viable path forward, we first undertake a series of model robustness checks per the routine devised by Young and Holsteen (2017). These checks are designed to reveal the stability of estimates across model specifications, providing some empirical grasp of the potential effects of multicollinearity and omitted variable bias. First, using the prevailing literature, we decide on a core set of theoretical and control variables that should be included in our models of Trump support. These include: partisanship, ideological self-identification, racial

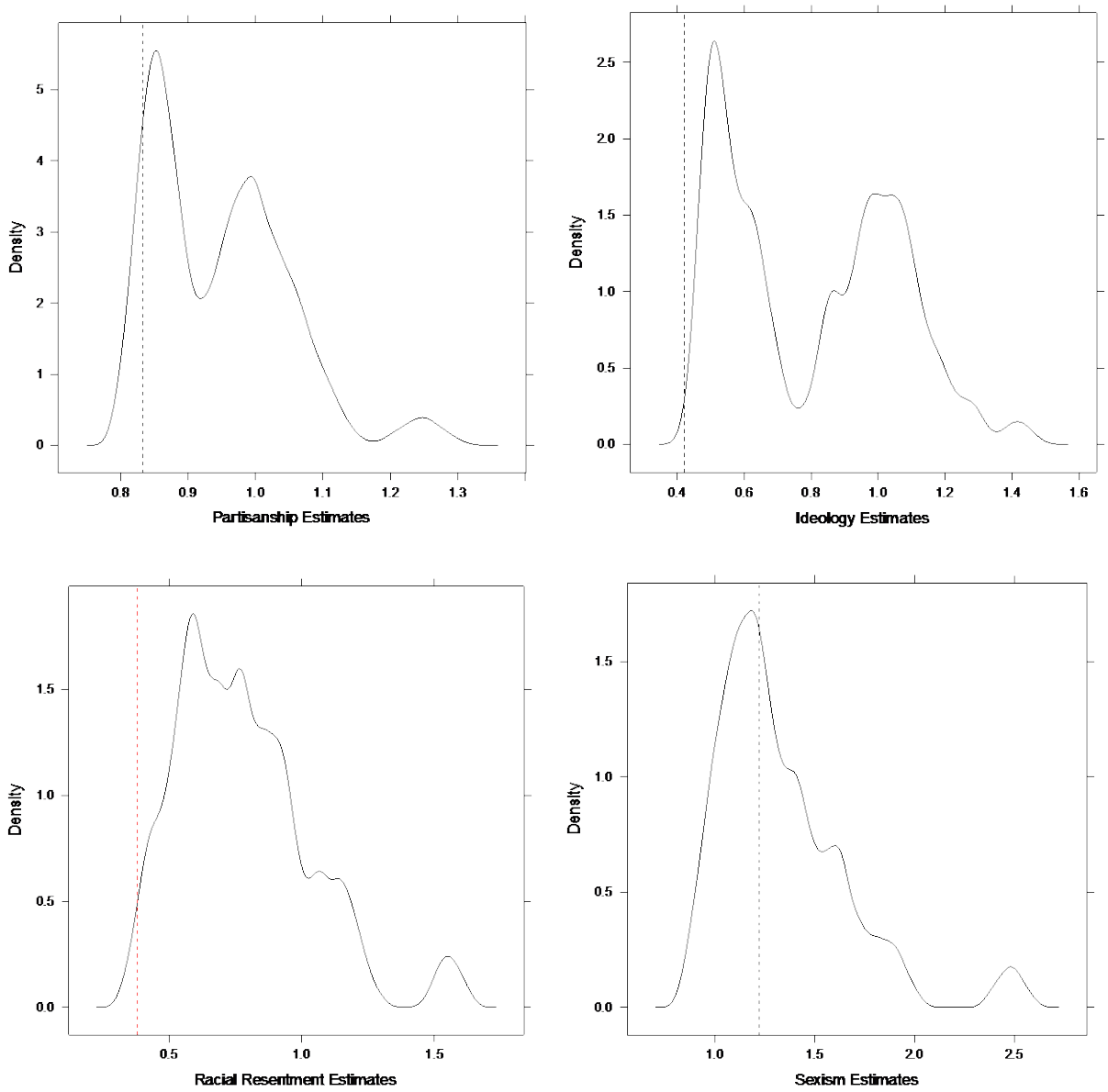
resentment, anti-immigrant attitudes, sexism, anti-PC attitudes, conspiracy thinking, income, educational attainment, age, frequency of attendance of religious services, and dummy variables for self-identification as black, white, or Hispanic, gender, and residence in the South. Then, we specify regression models with all possible combinations of these variables. This results in 2^{15}, or 32,768, specifications of models explaining Trump support. Finally, retained estimates associated with each variable of interest are used to construct those variables' "modeling distributions" – distributions where variability in coefficient estimates is attributed to different model specifications, rather than sampling error (such as in a sampling distribution).

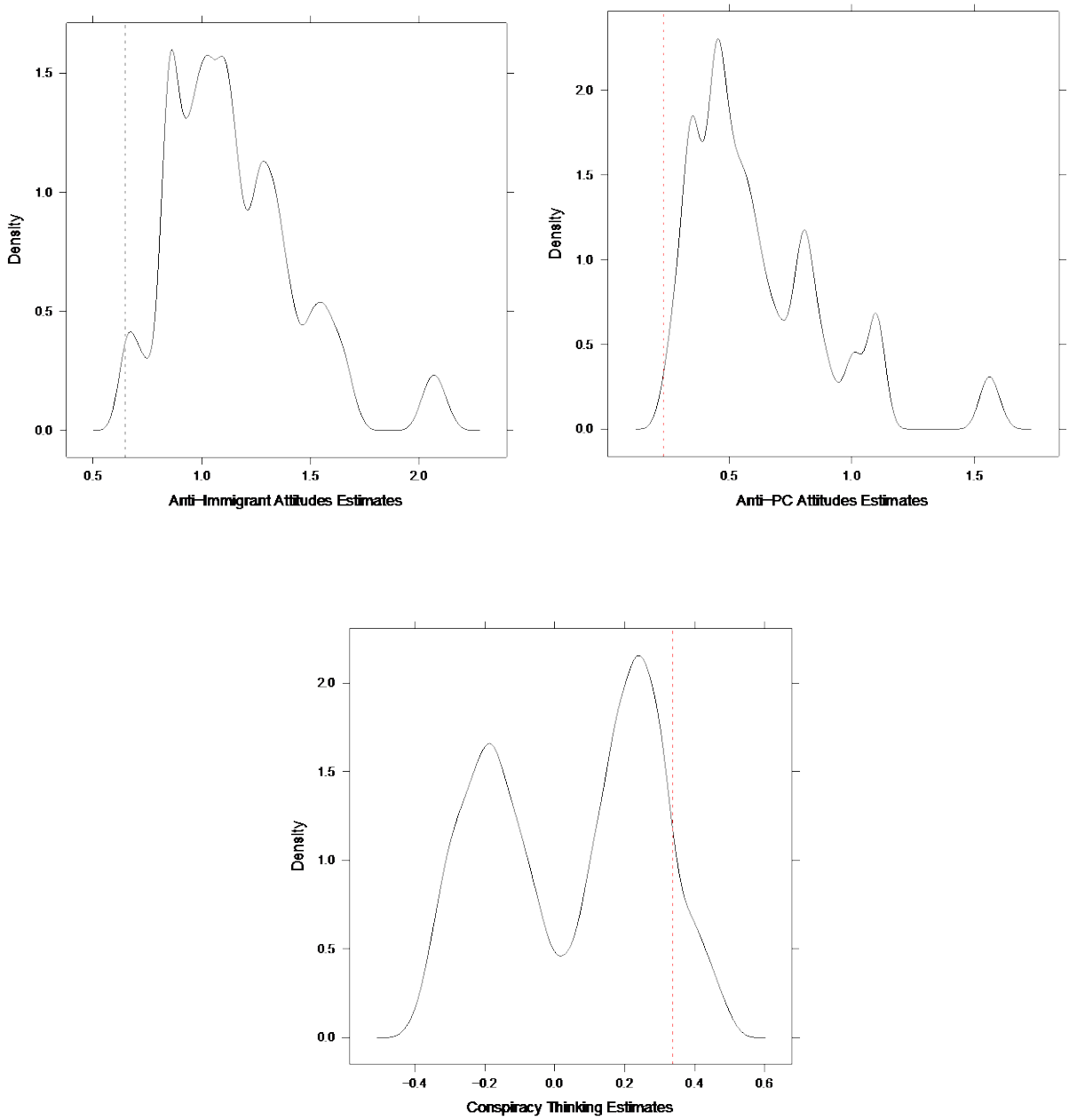
We are particularly interested in the shape of the empirical modeling distributions, including variance in the magnitude, sign, and statistical significance of the effect of a given variable across models. Relatively high instability according to the former criteria would suggest a large effect of some combination of multicollinearity and omitted variable bias. Substantively, this scenario would suggest that previous attempts to investigate explanations for Trump support may be inaccurate – or, at least, incomparable – unless all of such predictors are included in the model. In other words, investigations of the effects of our variables of interest may be misleading if controls for other explanatory factors are excluded from models.

Figure 1 contains the empirical modeling distributions for each of the explanatory factors of interest from logistic regression models of Trump vote choice. There are some systematic characteristics of the set of distributions worth considering. First, most distributions are heavily skewed (e.g., racial resentment, sexism); some are even bimodal (e.g., conspiracy thinking, ideological self-identifications). More importantly, estimates from the full model – depicted by vertical dashed lines – rarely represent either the mean or median estimate (i.e., the center of the empirical modeling distributions). This signifies that omitted variable bias is present – removal

of a subset of predictors dramatically alters the magnitude of the estimated coefficients. Finally, three hypothesized predictors of Trump support – conspiracy thinking, racial resentment, and anti-political correctness attitudes – are not statistically significant (as denoted by red dashed lines) in the full model, despite non-zero coefficients in the vast majority of models.

Figure 1: Density plots of coefficient estimates from model robustness analyses. Dashed lines represent estimate from full model with all controls. Dashed lines presented in red signify a statistically non-significant estimate from the full model.





Per the discussion of Table 2, fluctuation in the magnitude, direction, and statistical significance of estimated effects is likely not due to measurement error. Rather, it appears that our inferences about the substantive impact of the predictors of Trump support are highly contingent on which of those predictors are included in the model. Of course, diagnosing the problem says nothing of how fix it. Including all hypothesized support variables in the model –

an improvement over the situation that others have found themselves in – still leaves us with the problem of multicollinearity. Note that the effects of racial resentment, conspiracy thinking, and political correctness attitudes are not statistically significant in the full model. However, we should not take this as a sign that Trump failed to activate racist, conspiratorial, or anti-change orientations; indeed, these are some of the most popular explanations for Trump support. While conservative estimates are generally more desirable than the overestimations created by omitted variable bias, such conservative estimates also leave us unable to adjudicate between the various reasonable, theoretically-informed accounts of the psychological foundations of Trump support.

Creating a Profile

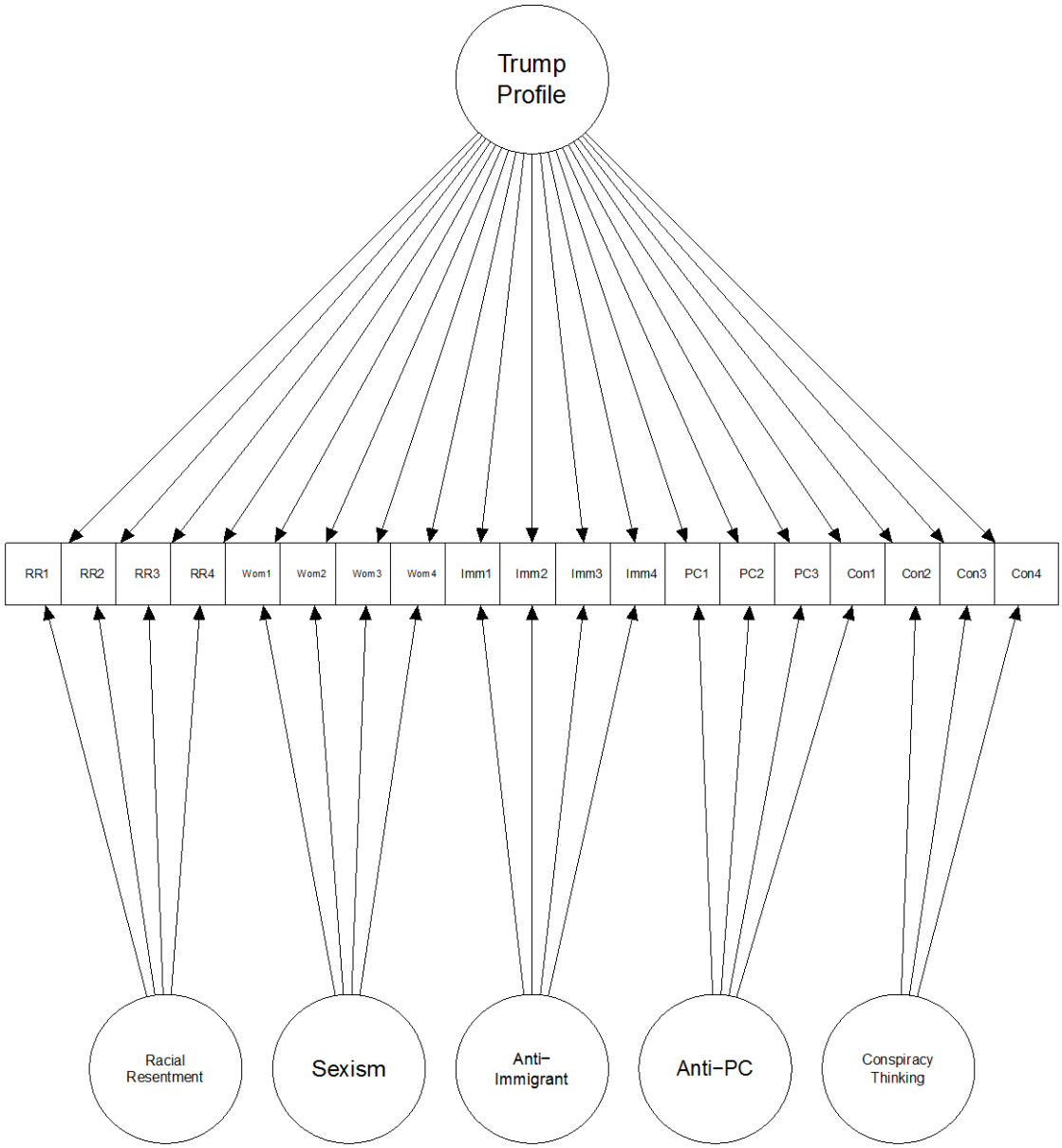
The solution to the remaining statistical problem lies in our understanding of the explanatory factors we are considering. Though researchers have proposed individual explanations for Trump's popularity, few would dispute the interrelation between most of those explanatory factors. Given that racial resentment, sexism, anti-immigrant attitudes, anti-PC attitudes, and conspiracy thinking are correlated, the observed attitudes used to capture these psychological orientations might be amenable to conceptualization as components of a broader "profile" of related, relevant attitudes. In other words, the observed correlations between these individual sets of attitudes – and the omitted variable bias and multicollinearity following from those correlations – is a consequence of a substantive relationship between the attitudes.

Conceptualization of a general orientation – or profile – that unifies the various attitudes associated with support for Trump is congruent with both the speculations of previous scholarship and the analyses presented thus far. It is theoretically parsimonious and, empirically, this reconceptualization of Trump support circumvents some of the problems associated with multicollinearity, resulting in a more powerful model. To understand the utility of this strategy,

consider that intelligence researchers going back to Charles Spearman have posited that intelligence is both theoretically and empirically composed of a general intelligence dimension, usually denoted "g," and many more individual dimensions that capture specific elements of intelligence, such as arithmetic ability and vocabulary. Modeling intelligence this way allows individuals to vary along specific dimensions of intelligence, while still allowing them to be oriented along a single, general intelligence continuum. This is precisely what we aim to do in modeling the social-psychological foundations of Trump support.

More specifically, we employ a bifactor model of the covariances between the observed indicators of racial resentment, sexism, anti-immigrant attitudes, anti-political correctness attitudes, and conspiracy thinking. A path diagram of the model we estimate appears in Figure 2. The specific explanatory factors related to Trump support are analogous to the specific dimensions of intelligence, and a general "profile" is analogous to general intelligence. Observed covariances between the individual indicators of racial resentment, sexism, anti-immigrant attitudes, anti-political correctness attitudes, and conspiracy thinking, are, theoretically, the causal product – to varying degrees – of both specific constructs of the same name and a general profile. Note that this model does not imply that racism, sexism, etc. are downstream byproducts of this profile, which would be better operationalized via a hierarchical model (e.g., a "second order" model). Rather, our hypothesis is that the specific observed attitudes – individual survey items – that we typically sum together and label racism, sexism, etc. can be amalgamated into a broader profile of attitudes that spans these constructs. This is a subtle, but crucial distinction for both our empirical strategy and theory. If this model fits the data well, we will have achieved a more parsimonious and theoretically-powerful account of Trump support, as well as circumvented the remaining statistical issue of high and consequential multicollinearity.

Figure 2: Path diagram depicting bifactor model of items capturing racial resentment, conspiracy thinking, anti-immigrant attitudes, sexism, and anti-political correctness attitudes. Latent variables (factors) in circles, observed indicators (survey items) in squares.



We report estimates from the bifactor model in Table 4. Several characteristics of the model output suggest excellent fit to the data. First, all but one factor loading (of 38 such estimated loadings) is statistically significant across specific factors, and all observed indicators significantly load on the Trump profile, albeit with varying degrees of strength. Moreover, all fit statistics suggest excellent model fit. The root mean squared error of approximation (RMSEA) is

at the recommended 0.05 cutoff for "excellent" model fit (Kline 2015), and both the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are above the recommended 0.95 rule of thumb (Hu and Bentler 1999).

Table 4: Estimates from bifactor model. Cell entries are standardized MLE coefficients.

	Profile Factor	Racial Resentment	Sexism	Anti-Immigrant Attitudes	Anti-PC Attitudes	Conspiracy Thinking
Racial Resentment						
RR1	0.785*	0.382*				
RR2	0.757*	0.423*				
RR3	0.747*	0.398*				
RR4 .	0.767*	0.339*				
Sexism						
Wom1	0.349*		0.555*			
Wom2	0.791*		0.117*			
Wom3	0.422*		0.322*			
Wom4	0.679*		0.101			
Anti-Immigrant Attitudes						
Imm1	0.708*			0.206*		
Imm2	0.727*			0.227*		
Imm3	0.840*			0.394*		
Imm4	0.748*			0.344*		
Anti-PC Attitudes						
PC1	0.739*				0.406*	
PC2	0.800*				0.442*	
PC3	0.600*				0.472*	
Conspiracy Thinking						
Con1	0.280*					0.738*
Con2	0.095*					0.488*
Con3	0.121*					0.586*
Con4	0.143*					0.840*
Fit Statistics						
χ^2 (133 df), p-value			338.858, 0.000			
RMSEA			0.050			
Prob(RMSEA $\leq$ 0.05)			0.452			
SRMR			0.035			
CFI			0.971			
TLI			0.963			
n			601			

Standardized MLE coefficients. * $p < 0.05$ level with respect to a two-tailed test.

We next consider concurrent validity – the extent to which the Trump profile[2] is capable of distinguishing between groups it should theoretically be able to distinguish between. In Figure 3, we plot the distribution of the Trump profile by gender, race, educational attainment, and household income. The patterns we observe are consistent with previous polling and analyses of Trump's electoral base. For example, men and whites are higher along the profile than women or non-whites. Likewise, those low in educational attainment and household income are higher along the profile than those with higher levels of education and household income, despite the bimodality of the higher income group.

Before considering the predictive validity of the Trump profile, we note that the profile is not merely a substitute for partisanship or ideology. We plot the distribution of the Trump profile by partisanship and ideology in Figure 4. Even though we expect the Trump profile to be related to partisan and ideological identities, we should anticipate neither that all Republicans/conservatives exhibit consistently high levels of the various ingredients of the profile, nor that all Democrats/liberals exhibit consistently low levels of the ingredient. Rather, we expect that a non-trivial proportion of conservatives and Republicans will be positioned low on the Trump profile, while a non-trivial proportion of liberals and Democrats will be positioned middling or high. Moreover, moderates and independents should be oriented at all locations along the latent continuum. The findings in Figure 4 meet these expectations. For example, 21% of Democrats lie in the upper half of the scale, and over 36% of Independents are in the lower half. Thus, the Trump profile is related to partisanship and ideology, but far from determinative of, or determined by, them.

[2] The profile is estimated by the model-predicted factor scores.

Figure 3: Distribution of the Trump profile by gender, race, educational attainment, and household income.

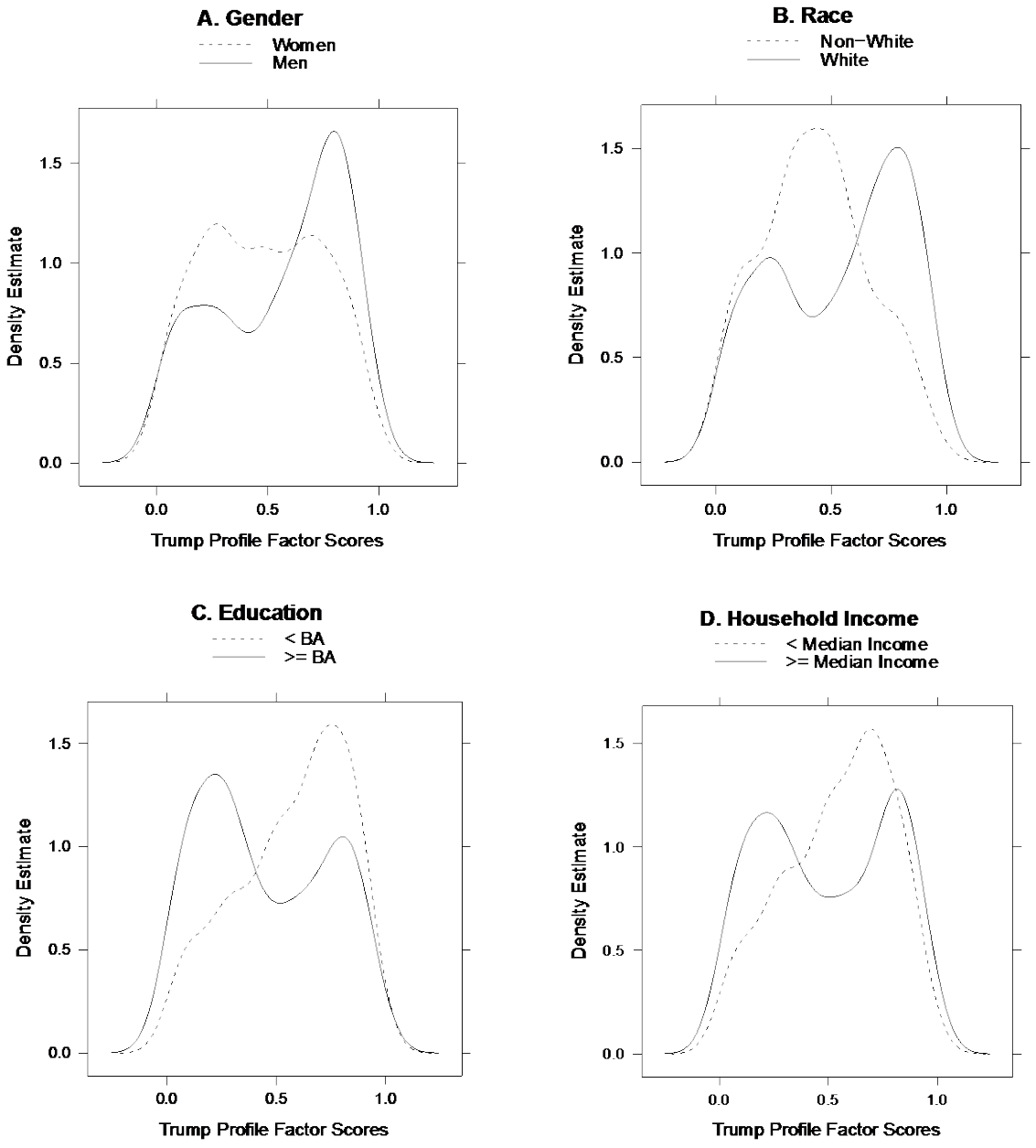
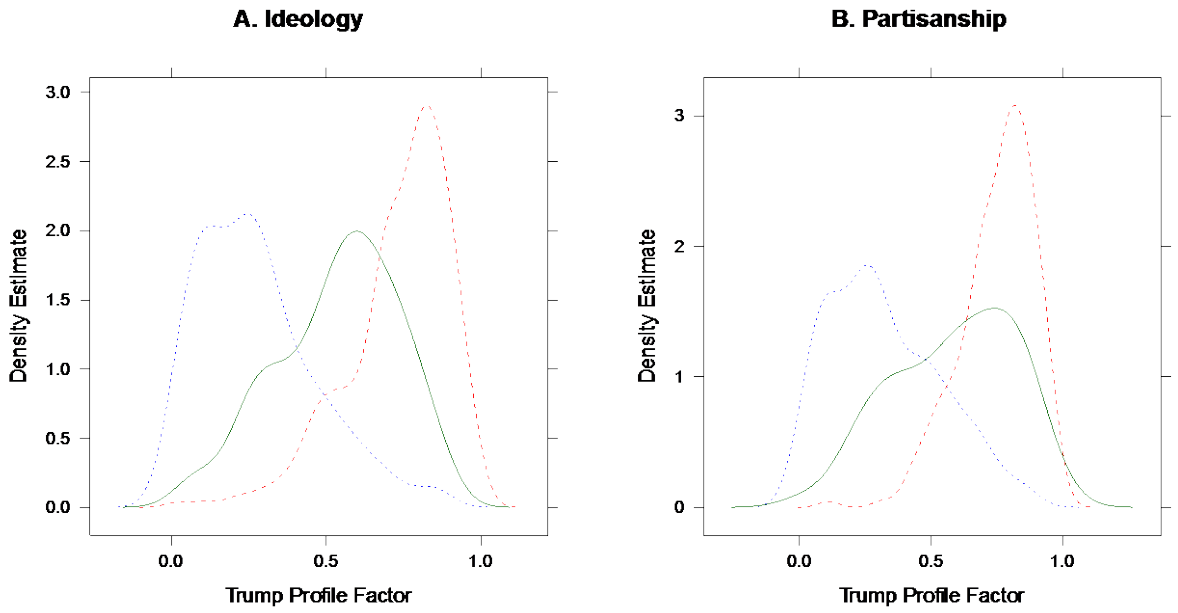


Figure 4: Distribution of the Trump profile, by self-identification as a liberal/Democrat (blue, dotted), conservative/Republican (red, dashed), or moderate/Independent (green, solid).



Predicting Support for Trump and Related Sentiments

We now demonstrate the predictive power of the Trump profile. We do so with respect to both specific measures of Trump support (self-reports of voting for, and feelings toward, Trump) and issues promoted by Trump: climate change denial, skepticism about Trump/Russia collusion, and distrust of the news media. Strong and significant effects of the Trump profile variable will not only provide a final piece of predictive validity for the measurement strategy but demonstrate the statistical and substantive utility of reconceptualizing the many explanations for Trump support as components of a single, broader profile.

First, we regress Donald Trump feeling thermometer scores (0-100) and (retrospective) Trump vote choice on the Trump profile, as well as partisanship, ideology, and a host of controls for retrospective evaluations of the national economy, income, religiosity, educational

attainment, age, race/ethnicity, gender, and residence in the South.[3] Ideology, partisanship, and the Trump profile are all coded such that larger values denote more conservative, Republican, and Trump-sympathetic orientations. Full model results appear in the Appendix, but model-based predictions over the range of the three explanatory variables of interest appear in Figure 5.[4]

The coefficients on the explanatory variables of interest are statistically significant and are larger than those associated with any of the other control variables in the model, including education or income. Of course, it makes good sense that both partisanship and ideology are important factors in explaining support for Trump. However, both ideology and, to a lesser extent, partisanship exhibit less predictive power than the Trump profile. Take, for instance, the predicted probability of a vote for Trump over Clinton or another candidate in panel A of Figure 5. For the strongest Democratic identifiers, this probability is about 0.30; for the strongest Republicans, about 0.60. However, for the Trump profile, those low on the scale voted for Trump with a probability of 0.13, and those very high with a probability of 0.70. A similar trend holds for Trump feeling thermometer scores in panel B, though the effects of partisanship and ideology more closely approximate that of the Trump profile.

The Trump profile also provides substantively and statistically significant predictive power in explaining attitudes about issues that Trump has regularly broached. In a final test of our analytic strategy, we regressed attitudes regarding skepticism about Russian interference in the 2016 presidential election, denial of climate change, and distrust of the media on the Trump profile, partisanship, ideology, and the control variables. Full model estimates appear in the

[3] All variables were rescaled to range from 0 to 1.
[4] Here and below all interval and ordinal variables were held at their mean values, and nominal at their modal values, in generating model-based predictions.

Supplemental Appendix, and model predictions over the range of the Trump profile and partisanship appear in Figure 6.

Figure 5: Predicted Trump feeling thermometer scores and probability of Trump vote choice, across the range of partisanship, ideological self-identifications, and the Trump profile, controlling for other factors. Dashed lines represent 95% confidence intervals.

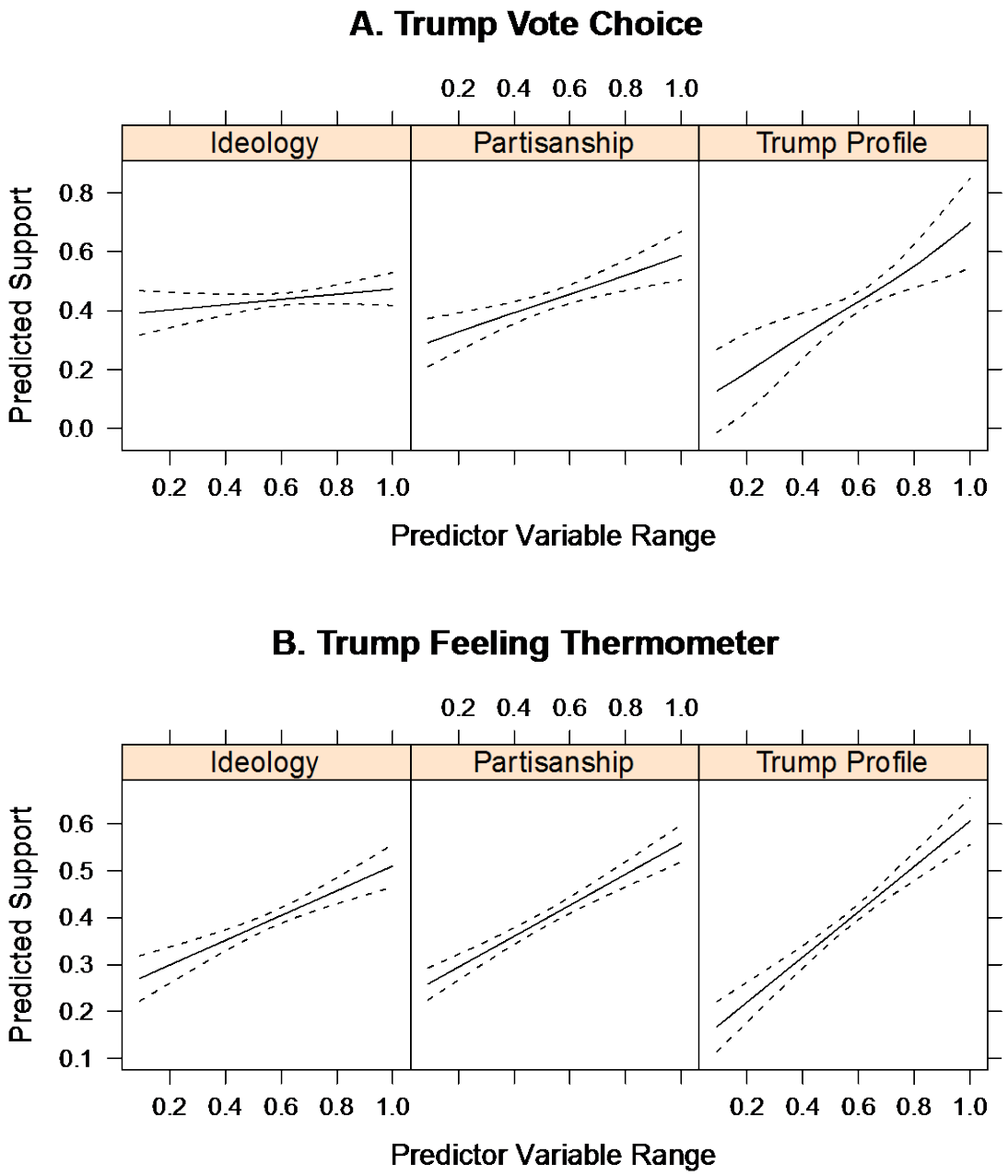
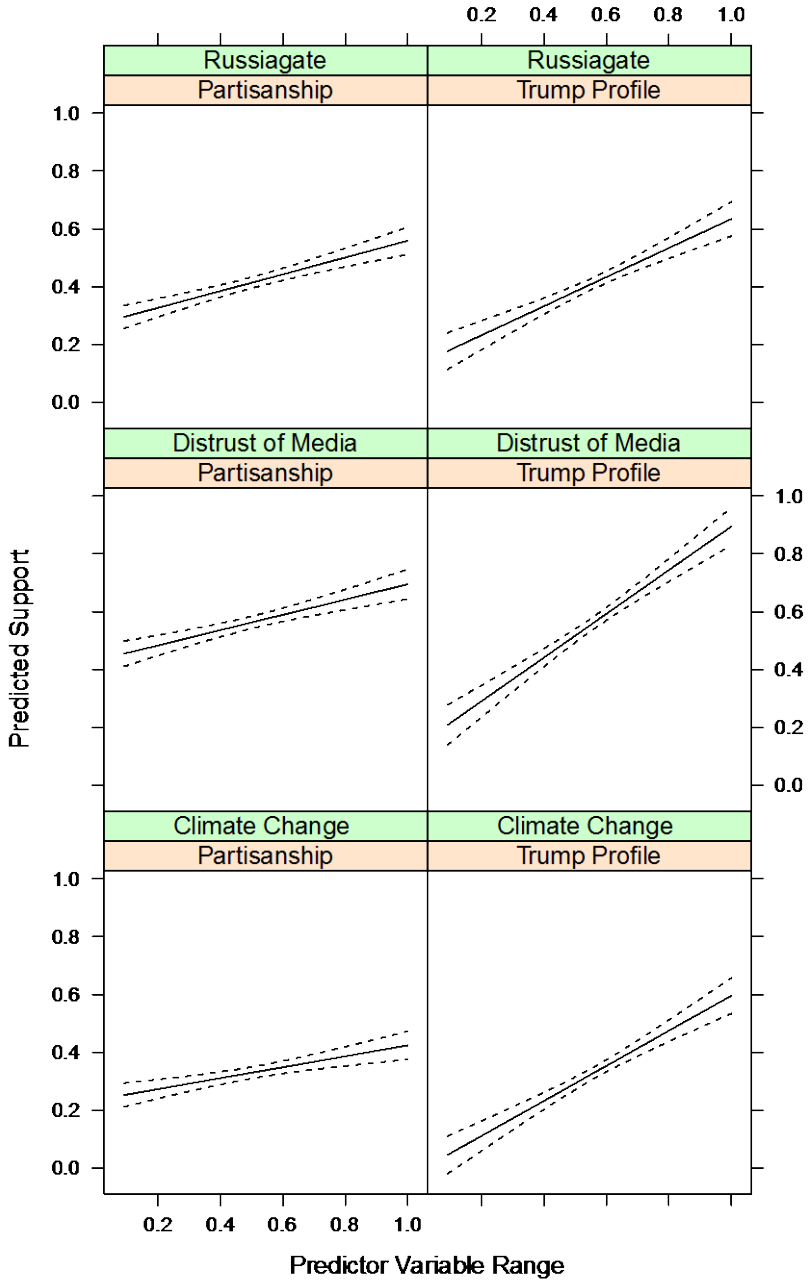


Figure 6: Predicted distrust of media, skepticism of anthropogenic climate change, and disbelief in Russian collusion in the 2016 presidential election across range of the Trump profile and partisanship, controlling for other factors. Dashed lines represent 95% confidence intervals.



Here again, we observe substantively large effects of the Trump profile in explaining attitudes associated with Trump's espoused stances on key issues. Those low on the Trump profile strongly agree that "climate change is real and caused by manmade carbon emissions,"

agree that "the Russians colluded to rig the 2016 presidential election," and disagree that "much of the mainstream news is deliberately slanted to mislead us." Those high on the Trump profile exhibit the opposite attitudes. The Trump profile is also more predictive of these attitudes than are either partisanship (pictured) or ideology.

Trump Profile or Conservative Profile?

Finally, we consider both the robustness of the profile approach, as well as the discriminatory power of the Trump profile when it comes to other Republican candidates. In order to demonstrate the robustness of our profile-based approach to measuring Trump support, we replicate as closely as possible the previous analyses using the 2016 ANES, which included many of the variables utilized above. Of those, most are either direct replications or substantively identical (see Supplemental Appendix). Additionally, the 2016 ANES included items designed to measure authoritarianism, an oft-cited reason for Trump support (e.g. MacWilliams 2016) not available on the CCES, though it does not include a measure of conspiracy thinking. Moreover, the 2016 ANES includes measures of attitudes about other issues that Trump has claimed ownership over, as well as self-reported Republican primary voting. The latter information is useful for establishing that the Trump profile is specific to Trump and not merely a substitute for traditional conservative principles or "mainstream" Republicanism.

The bifactor model again fits the data well.[5] As with the 2018 CCES data, all fit statistics meet their respective rules of thumb and all indicators load statistically significantly on the Trump profile factor. Moreover, we observe similar relationships between the Trump profile and measures of support for Trump and Trump-related issues. Figure 7 depicts the relative influence of partisanship, ideology, and the Trump profile on feelings toward Trump and Trump vote

[5] Full model estimates appear in the Supplemental Appendix, as do distributions of the Trump profile stratified by partisan and ideological self-identification.

choice in the general election. Although the effects of the Trump profile and partisanship are slightly more comparable than we observed using the 2018 CCES, the effects of the Trump profile rival those of partisanship and prove greater than those of ideology.

Figure 7: Predicted Trump feeling thermometer scores and probability of Trump vote choice, across the range of partisanship, ideological self-identifications, and the Trump profile, controlling for other factors. Dashed lines represent 95% confidence intervals. 2016 ANES data.

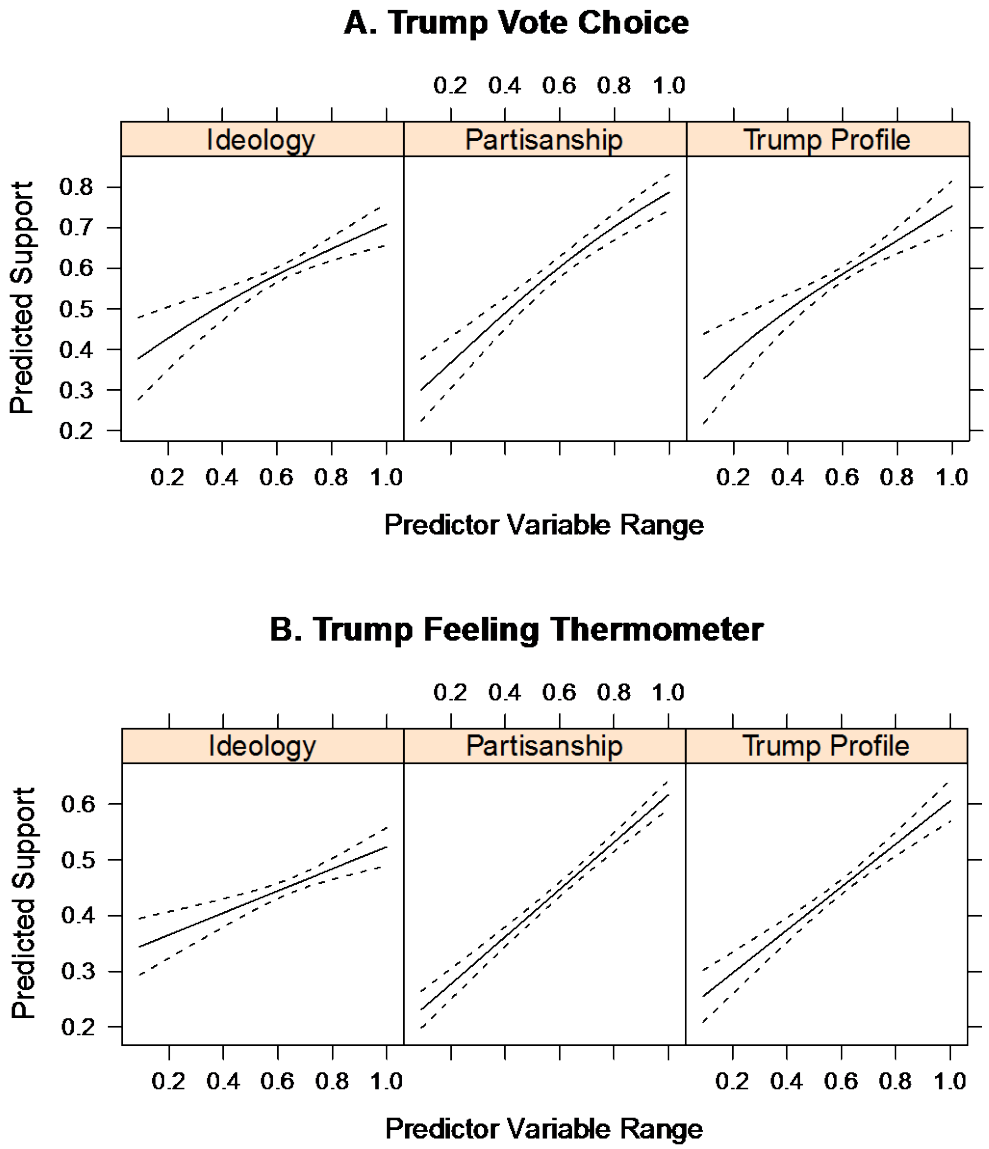


Figure 8: Predicted skepticism of anthropogenic climate change, perceived danger of childhood vaccinations, and supportive attitudes about building a wall along the U.S.-Mexican border across range of Trump profile and partisanship, controlling for other factors. Dashed lines represent 95% confidence intervals. 2016 ANES data.

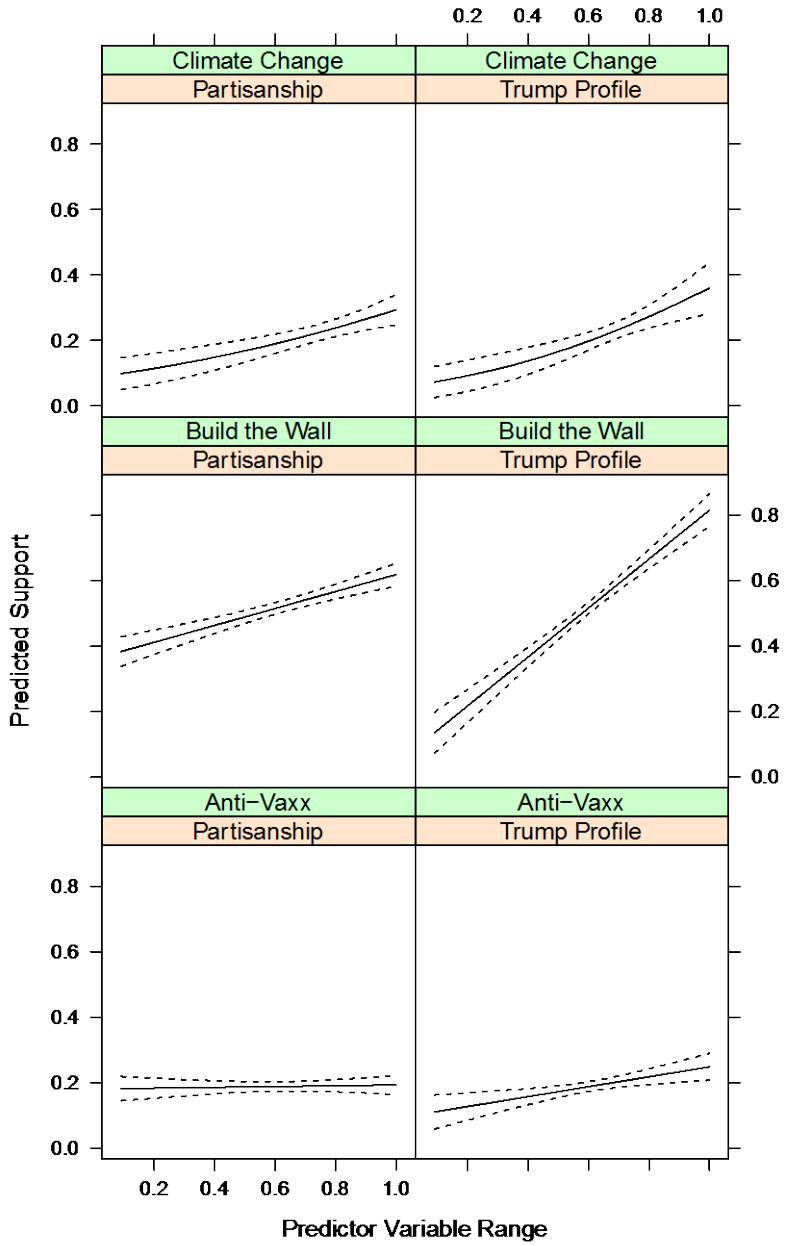


Figure 8 shows that the Trump profile is, again, highly predictive of attitudes about Trump-related issues, even compared to partisanship, holding other factors like ideology and sociodemographic characteristics constant. In each case, the Trump profile provides more

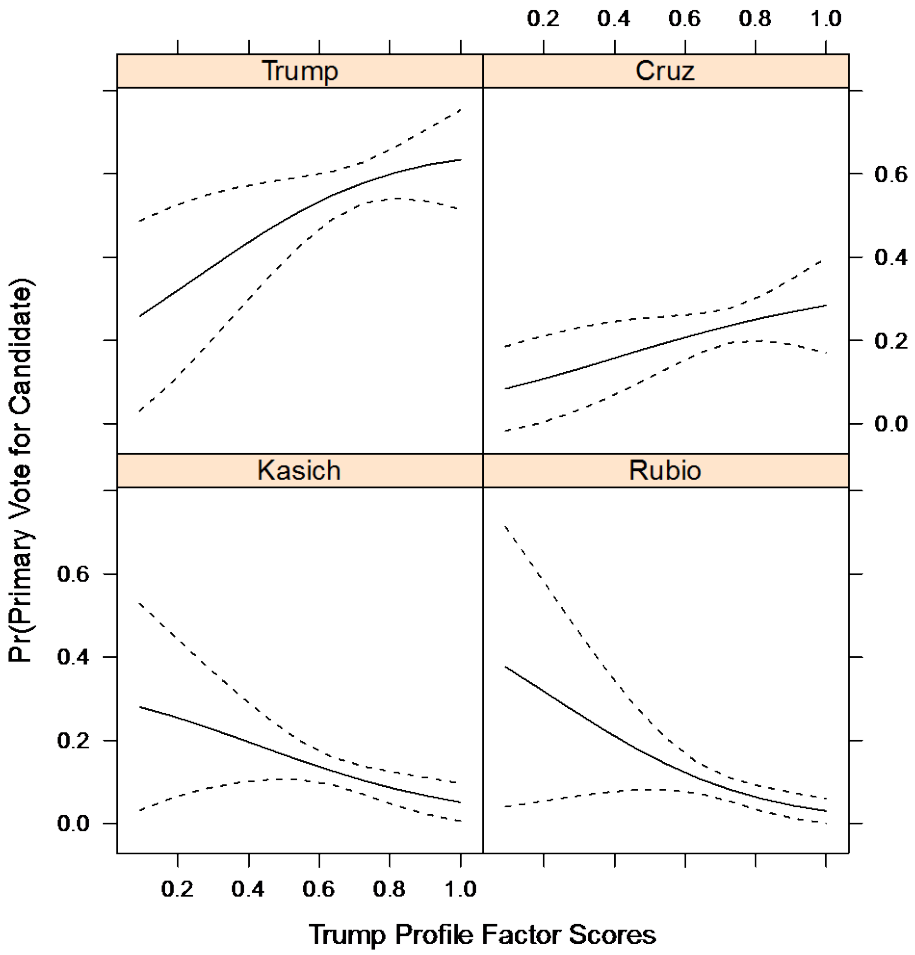
explanatory power than either partisanship (pictured) or ideological self-identifications. This is most apparent when it comes to attitudes about "the wall" and childhood vaccinations, the latter of which is not statistically related to either partisanship or ideology.

Next, we consider the discriminatory power of the Trump profile. If this profile of attitudes is unique to Trump supporters, it should be more strongly related to voting for Trump than any other 2016 Republican primary candidate. To test this proposition, we estimate a multinomial logistic regression where the dependent variable captures voting for Trump, Ted Cruz, John Kasich, or Marco Rubio in the 2016 primary elections. The predicted probability of casting a vote for each of the candidates across the range of the Trump profile, holding constant the strength of partisan and ideological identities, retrospective evaluations of the economy, and sociodemographic characteristics, is depicted in Figure 9.[6]

Even among self-identified Republicans voting in the primary, the Trump profile is strongly positively related to voting for Trump.[7] We find a weak positive relationship between the Trump profile and voting for Cruz, as we might expect given his platform and rhetoric. However, such is not the case when it comes to the two mainstream candidates: Rubio and Kasich. For both of these mainstream Republican candidates, we observe a negative relationship between the Trump profile and candidate vote choice.

[6] Full model estimates appear in the Supplemental Appendix.
[7] The relatively wide confidence bands toward the low end of the Trump profile scale simply reflects that there was a wide range of plausible probabilities of voting for each of the candidates *among Republicans.* In other words, Republicans very high on the Trump profile were very likely to vote for Trump, and very unlikely to vote for Kasich and Rubio (Cruz is somewhere in the middle). Republicans very low on the Trump profile still may have voted for Trump, just as they may have voted for Kasich or Rubio.

Figure 9: Predicted probability of voting for each of four Republican candidates in the 2016 U.S. presidential primaries, controlling for other factors. Respondents are Republicans. Dashed lines represent 95% confidence intervals. 2016 ANES data.



In a final test of our strategy we compare various models of Trump support to gauge how well models including the Trump profile perform relative to other specifications found in the literature. In Table 5, we present Bayesian Information Criterion (BIC) estimates for three variations of the Trump affect and vote choice models from both the 2018 CCES and 2016 ANES. The "traditional" model includes partisanship, ideology, retrospective economic evaluations, and a host a sociodemographic controls for religiosity, race and ethnicity, educational attainment, income, gender, and residence in the South. Taking this as a baseline

model of sorts, we also specify models that add scales of each of the sets of items that compose the Trump profile ("Traditional + Individual Scales") or that simply add the Trump profile ("Traditional + Trump Profile"). Smaller model BIC estimates indicate better model performance – a combination of predictive power and parsimony (i.e., number of parameters estimated). In every instance, we observe a smaller model BIC for the Trump profile model over both the traditional and individual scale models. Thus, we possess supportive evidence that the Trump profile performs well comparatively, in addition to circumventing inferential issues related to omitted variable bias and multicollinearity and synthesizing theory about the psychological antecedents of Trump support.

Table 5: Model BIC fit statistics for various Trump support model specifications.

	BIC
Trump Thermometer, 2018 CCES	
Traditional	-124.8915
Traditional + Individual Scales	-208.3895
Traditional + Trump Profile	-212.0669
Trump Vote Choice, 2018 CCES	
Traditional	281.9763
Traditional + Individual Scales	268.3308
Traditional + Trump Profile	239.1279
Trump Thermometer, 2016 ANES	
Traditional	6.664764
Traditional + Trump Profile	-145.6906
The "Status Threat" Model	-199.7176
Trump Vote Choice, 2019 ANES	
Traditional	524.8026
Traditional + Individual Scales	483.4656
Traditional + Trump Profile	463.3405

Conclusion

A robust literature demonstrates that numerous attitudes and orientations, beyond usual suspects like partisanship and ideology, are related to support for Donald Trump. Elucidation of these specific factors has expanded the scope of the literature and provided a better accounting of Trump support, an important political phenomenon. In this manuscript, we sought to provide a more unified investigation of the many posited sources of support for Donald Trump that resulted in a sharper model of Trump support. To circumvent the problems associated with omitted variable bias and multicollinearity in modeling Trump support, both of which we empirically demonstrated, we generated a broader profile of attitudes related to the explanatory factors others have highlighted. This profile is highly predictive of voting for and feelings toward Trump, as well as attitudes about the U.S.–Mexico border wall, childhood vaccinations, distrust of the media, and climate change denialism, even controlling for partisanship, ideology, and other factors. The Trump profile does not, however, measure Republicanism or conservatism in another way: it is negatively associated with support for other Republican candidates in the 2016 primary elections. Finally, we found that inclusion of our profile of attitudes regarding racial groups, women, immigrants, PC culture, and conspiracy theories constituted a better model of Trump support than either classical vote choice specifications or those that include all individual explanatory factors separately.

Our approach is useful, first, because it obviates the necessity of scholars to accept the consequences of either multicollinearity or omitted variable bias in their models of vote choice. Using our measurement strategy, both problems are avoided. Second, our strategy is likely more congruent with reality. Even though previous work makes a strong case for specific explanatory factors, it is unlikely that any given factor on its own explains all Trump supporters. By

generating a profile of attitudes Trump is suspected of activating, we are more likely to account for the myriad combinations of attitudes and orientations that make Trump an attractive candidate. For example, while some strong Trump supporters may exhibit high levels of racial resentment and xenophobia, they may be low in sexism and middling in conspiracy thinking. This profile of attitudes is possible using our strategy and may still result in a relatively high position along the Trump profile factor.

More broadly, our findings suggest that much of what political scientists have learned about political behavior in the last 100 years is contingent on mainstream parties supporting mainstream candidates who stick to mainstream party platforms. Facing a crowded primary field, it was entrepreneurial for Trump to activate existing attitudes among the mass public that other candidates avoided (Sides, Tesler and Vavreck 2018). Unfortunately for an increasingly uncivil political culture marred by polarization and sorting, his tactics proved effective. Recent elections have seen other candidates mimicking Trump's language and policy stances, in the U.S. and abroad. Strategic politicians do not have behave like Trump in order to activate in people what Trump has managed to activate, or to find his successes.

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