On Modeling Support for Donald Trump

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Why do Americans support Donald Trump? Scholars have identified many factors correlated with support for Trump, but attempts at modeling these factors suffer from either multicollinearity, on the one hand, or omitted variable bias, on the other. Both obscure inferences. Using two national surveys, we demonstrate the perils of including or failing to include many of these factors in models. We then reconceptualize the sources of Trump support as components of perceived status threat; this "profile" of factors (e.g., attitudes towards women, minorities, and political correctness) strongly predicts Trump vote choice and general support, as well as attitudes about issues connected to Trump, controlling for other factors. Moreover, this profile outperforms partisanship and ideology as predictors of Trump support in most cases and is negatively related to support for mainstream Republican candidates. Our analyses suggest that Trump activated longstanding grievances that transcend traditional party cleavages.

Keywords: Donald Trump, Partisanship, Racism, Sexism, Political Correctness, Bifactor Model

Word Count:

Donald Trump entered the 2016 Republican primary without political experience, the support of party elites, or a record of espousing conservative policies. His administration has been engulfed by scandal, he continually flouts democratic norms, and his rhetoric consists of racist, sexist, and xenophobic appeals (Carey, et al. 2019). Why did Americans vote for Trump and why do more than 40 percent of Americans continue to support him?

Researchers have embraced the idea that Trump's support derives from different factors than does support for typical Republican candidates (Reny, Collingwood and Valenzuela 2019, Barber and Pope 2019, Blum and Parker 2019). Thus, understanding the sources of Trump's support has become "a key social-science challenge" (Federico and de Zavala 2018, 110), and a developing research agenda seeks to identify the sources of Trump's support (Grossmann 2019).

The numerous factors identified as driving Trump support (e.g., negative attitudes towards minorities, women, and immigrants) raise concerns not only because they comprise a "toxic brew" (Bartels 2016), but because they can be activated by strategic politicians (Cohen and Smith 2016), much the way mainstream candidates activate partisan identities (Zaller 1992). We argue that such attitudes, or grievances, are expressions of crescendoing feelings of status threat that have long been hiding in plain sight (e.g., Hofstadter 1964, Adorno, et al. 1950, Lane 1962), mentioned by prominent political scientists (Achen and Bartels 2017, 265, Campbell, et al. 1960, ch. 15), but "underestimated" in relation to the fundamentals, like partisanship (Grossmann 2019, 2). Trump eschewed traditional Republican appeals and instead exploited these longstanding grievances to "hunt where the ducks were" (Sides, Tesler and Vavreck 2018).

Trump's tactics caught social scientists off-guard, and without survey instruments to adequately understand his support until it reached an apex. As a consequence, the literature paints both an overly complicated and incomplete picture. Scholars have identified numerous

factors explaining Trump support, ranging from political and sociological factors (e.g., partisanship; education), to a series of uncharitable social-psychological traits (e.g., racism). However, accurate estimates are obscured because these factors are strongly correlated, leading models to be plagued either by multicollinearity, where many of such factors are present, or omitted variable bias, where many are missing.

In this study, we first 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. We then reconceptualize the sources of Trump support as components of a broader orientation animated by perceived status threat (Mutz 2018b, Blum and Parker 2019). Using unique data from the 2018 Cooperative Congressional Election Study (CCES) and publicly available data from the 2016 American National Election Study (ANES), we determine that because voters may express status threat in multiple ways, a complete examination of Trump's support requires both (1) a majority of the posited sources of Trump support on singular surveys and (2) a reconceptualization and unification of the sources of Trump support as a broad orientation.

Status threat, we argue, is the source of variation that weaves this profile of attitudes towards racial and gender groups, immigrants, political correctness, and elites together. We show that this orientation, or "profile," strongly predicts voting for Trump in 2016, favoring Trump in 2018, and attitudes about Trump's core issues. This profile outperforms traditional predictors of vote choice, such as partisanship and ideology. Further, this profile does not merely capture Republicanism or conservatism in another way; it is negatively correlated with support for establishment Republican candidates. These findings are not just theoretically and methodologically informative, but politically important because, as scholars have observed

(Nyhan 2016), Trump's tactics "may set in motion… a clash between an overwhelmingly white ethnic party and a cosmopolitan coalition of minority groups and college-educated whites."

The Many Hypothesized Predictors of Support for Donald Trump

Since 2016, scholars from across disciplines have attempted to explain why so many Americans support Donald Trump. The hypothesized factors begin with the traditional political predictors: Republicanism, conservatism, and negative views toward the Obama economy strongly predicted the Trump vote (Bartels 2018, Bartels 2016, Abramowitz and McCoy 2019). Such findings are consistent with a large body of political science literature (Achen and Bartels 2017). Other analyses points to sociological factors: education, for example, is negatively associated with support for Trump (Silver 2016) and several studies suggest that the white working class, responding to a sense of economic vulnerability, was a major factor in Trump's victory (Bucci 2017, Morgan and Lee 2018, Morgan 2018, McQuarrie 2017). However, while Trump voters appear nationally poor, locally they tend to be financially well-off relative to their geography (Ogorzalek, Piston and Puig 2019, see also Rothwell and Diego-Rosell 2016), throwing some doubt onto proposed socio-economic explanations. Trump and his supporters exhibited something beyond adherence to Republican issues or economic concerns.

Trump's rhetoric was, at times, racist, sexist, xenophobic, anti-PC, authoritarian, conspiratorial, and populist (Finley and Esposito 2019), and voters who shared Trump's espoused ideas tended to vote for him (Sherman 2018). This suggests that Trump was tapping into longstanding grievances that had been observed previously (Alberta 2019, Parker and Barreto 2014, Cramer 2016).

Given the ability of racially-charged rhetoric to activate racial attitudes (Tesler 2017), researchers have found evidence that Trump's rhetoric activated various forms of racism and racial resentment toward African-Americans, Muslims, and Mexicans (2018, Luttig, Federico and Lavine 2017, Schaffner, Macwilliams and Nteta 2018, Engelhardt 2019, Abramowitz and McCoy 2019, Lajevardi and Oskooii 2018, Donovan and Redlawsk 2018). In addition, Trump voters also displayed evidence of racial anxiety (Abramowitz 2018, Craig, Rucker and Richeson 2018, Fording and Schram 2017) and strong self-identification as whites (Sides, Tesler and Vavreck 2019, Inwood 2018, Major, Blodorn and Major Blascovich 2018, Jardina 2019, Lopez Bunyasi 2019). Other scholars have found that attitudes about immigrants and immigration were as powerful as racial attitudes in determining the Trump vote (Manza and Crowley 2018, Hooghe and Dassonneville 2018) and that attitudes about both race and immigration played a greater role in determining the vote in 2016 than in previous elections (Sides, Tesler and Vavreck 2017, Donovan and Redlawsk 2018, Newman, Shah and Collingwood 2018, Reny, et al. 2019).

Attitudes toward women have also been found to predict Trump support (Bracic, Israel-Trummel and Shortle 2019, Frasure-Yokley 2018, Schaffner, et al. 2018, Setzler and Yanus 2018), with more sexist attitudes relating to higher support. Trump's gendered rhetoric appear to have activated existing gender-based attitudes in Trump's favor (Cassese and Holman 2019), and in a way that has not been observed in previous elections (Valentino, Wayne and Oceno 2018).

Broader worldviews have also been shown to predict Trump support. Much of Trump's rhetoric flouted discursive norms by explicitly invoking racism, sexism, and xenophobia (Maskovsky 2017), and researchers experimentally find that "temporarily priming PC norms significantly increased support for Donald Trump" (Conway, Repke and Houck 2017). As such, negative attitudes toward political correctness predict Trump support. Also in line with Trump's

style of rhetoric (Oliver and Rahn 2016), researchers identified populism (Carmines, Ensley and Wagner 2016, Aydın-Düzgit and Keyman 2017) and conspiracy thinking (Cassino 2016) as associated with support for Trump. Finally, given the connection between authoritarianism and supporting candidates who espouse authoritarian ideas (Cohen and Smith 2016), Trump's "strong-man" image elevated authoritarian views in relation to previous elections (Knuckey and Hassan 2019). Numerous studies show that various operationalizations of authoritarianism are positively associated with Trump voting and Trump support (Choma and Hanoch 2017, Crowson and Brandes 2017, Womick, et al. 2018, Ludeke, Klitgaard and Vitriol 2018, MacWilliams 2016a).

Scholars have added immensely to our knowledge by identifying these numerous factors associated with voting for and supporting Trump. It is perhaps time for political scientists, rather than prioritizing the search for more factors related to Trump support, to take stock of these previously identified factors. As other scholars have noted and as we will demonstrate, these aforementioned factors are highly correlated, suggesting that they spring from the same well. As such, it is perhaps more efficient to conceptualize all of these factors as a profile, rather than as individual explanations where only one can be correct. Next, we propose a theoretical framework for more parsimoniously accounting for all of these correlated factors, and then develop an empirical strategy for modeling Trump support.

Status Threat: Sewing It All Together

The above factors hypothesized to drive Trump support have been shown to be themselves expressions of a deep-seated orientation. Previous authors have argued racial resentment (Tesler 2016, 46), anti-immigrant attitudes (Parker and Barreto 2013, Albertson and

Gadarian 2015), populism/conspiracy thinking (Uscinski and Parent 2014, Gidron and Hall 2017), sexism (Valentino, et al. 2018), anti-PC attitudes (Lalonde, Doan and Patterson 2000), and authoritarianism (Hetherington and Suhay 2011) can all be at least partially explained by status threat, albeit of different flavors and intensities. Indeed, others have observes that support for Trump stems from an array of attitudes mixed with anxiety (Pettigrew 2017, Donovan and Redlawsk 2018), and that intolerance and feelings of threat are intermingled (Feldman 2017). Moreover, numerous seminal works of social and political psychology note that pre-partisan factors may play an important role in determining political attitudes and behaviors (Adorno, et al. 1950, Hofstadter 1964, Lane 1962).

These factors are longstanding cultural and demographic dispositions, not created by Trump, but rather exploited by him (Abramowitz and McCoy 2019, Sides, et al. 2018). The attitudes stemming from status threat can be activated by and connected to political choices by strategic politicians; Trump simply captured voters who had broad aversion to social change which was not being activated by other candidates (Grossmann and Thaler 2018).

Being confronted with social change triggers support for Trump. For example, areas that experienced significant Latino population growth were more likely to support Trump in 2016, as compared to supporting Romney four years prior (Enos 2017, see also Craig and Richeson 2014). Other studies show that exposing whites to racial and ethnic minorities or to the advent of minority status heightens feelings of threat, increases support for anti-immigrant policies, decreases support for PC, and fosters greater intentions to vote for Trump (Major, et al. 2018, Knowles and Tropp 2018). Bonikowski (2017, 181) argues that "social changes have engendered a sense of collective status threat" and that such threat has been channeled into "resentments toward elites, immigrants, and ethnic, racial and religious minorities, thereby activating

previously latent attitudes and lending legitimacy to radical political campaigns that promise to return power and status to their aggrieved supporters."

Perceived status threat is a more charitable explanation for Trump support than outright racism, sexism, xenophobia or any of the other attributes often ascribed to Trump supporters. If people believe that their place in society is being taken, they may exhibit attitudes that seem racist, sexist, xenophobic, and conspiratorial, but such attitudes would not necessarily be born of a deep, antagonistic relationship with minority groups, women, or immigrants. Instead, people could exhibit a benign fear of change that is then channeled in ways that appear more sinister.

Thus, there can be variance in the theoretical "blame" for Trump support. Where labels such as "sexist" and "racist" connote an active hatred, our theory of perceived status threat provides for the possibility of passive orientations toward change, rather than at particular "others." Where racism, sexism, and the like must be assessed and challenged where we are certain they exist, making unnuanced charges of racism or sexism, for example, is to the detriment of toleration and civil discourse. Racism, sexism, xenophobia, conspiracy theorizing, and anti-PC sentiment, for example, while sometimes weakly correlated with partisan self-identifications, are hardly determinative of them: these attitudes exist across party lines.

We build one previous studies of status threat – which often focus on one particular type of status held by one particular group – and instead conceptualized status threat as a broader disposition that could be held by different people for differing reasons. After all, Trump support – as our analysis will reveal – is not confined to men, rural inhabitants, or even whites. Our contention is that the status threat at the center of Trump support is an amalgamation of statuses among a number of groups. Surely, perceived threats to socioeconomic status prompt concerns over illegal immigration or affirmative action. But, perceived threats to the status of America as

a global superpower can also explain anti-immigrant attitudes, for example. Most importantly, perceived threats to the status of American culture – the combination of traditionalism and nostalgia at the center of Trump's campaign message – have the potential to produce the aforementioned attitudes, as well as others. In other words, this profile of psychological factors posited to "explain" Trump support all stem from a perceived, broadly conceived threat to American civic life.

Perhaps this explanation runs the risk of too much generality (i.e., everything matters). This is a valid concern as falsifiability is crucial to the scientific enterprise. However, this theory is empirically testable; moreover, it simplifies competing theories of Trump support, thereby emphasizing a different scientific goal: parsimony. Thus, we suggest a reconceptualization of the sources of Trump support, unifying them along a broader, deeper dimension of public opinion.

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 on single surveys. Therefore, we fielded a unique module of items on the 2018 Cooperative Congressional Election Study (CCES) that included indicators to estimate attitudes towards racial minorities, women, immigrants, political correctness, and elites/conspiracy thinking. Question wording appears in Table 1. The survey was administered to 1,000 respondents during October 2018. While this data was collected two years after the 2016 election, we see little reason to expect that the predictors of Trump support have radically changed over time. The predictors that researchers have posited are deep-seated attitudes and orientations, meaning there is little reason to expect that these factors have changed in their absolute level, or in their correlation with Trump support. That

said, we also employ the 2016 American National Election Study (ANES), which included similar survey instruments, with two particular goals in mind: 1) to test the power of our analytical strategy, 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.

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

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.

Sexism

1) Women should earn the same wages as their male counterpart.
2) A woman's place is in the home.
3) he 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-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.

The analytical strategy we take unfolds in four steps. First, 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 better strategy for conceptualizing and measuring the Trump support factors which results in an empirical estimate of a Trump "profile" – an amalgamation of the factors posited to explain support for Trump. Third, we demonstrate that the Trump profile is a better predictor of Trump support and attitudes associated with Trump than any individual factor alone, or all factors separately applied. Finally, we estimate the Trump profile using a close approximation of variables from the 2016 ANES, confirming the existence and predictive power of the Trump profile, and showcasing its ability to discriminate between support for Trump and other Republican presidential candidates.

Empirical Analysis

Each of the factors posited to explain Trump support, excepting partisanship and ideology, are measured via multiple-item scales. This strategy allows us to reduce measurement error and employ sharper estimates of the latent variables of interest. 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) unbiased 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 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[1] and squarely unidimensional. Thus, these variables will be on a

[1] The sexism scale is slightly below the 0.70 cutoff that people tend to employ. We are not, however, particularly concerned about this for three reasons. First, the alpha reliability estimate is only trivially lower than the 0.70 cutoff

roughly equal playing field in terms of the influence of measurement error when comparing effects in models presented below.

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
Conspiracy Thinking	4	0.774	0.896
Anti-Immigrant Attitudes	4	0.847	0.957
Sexism	4	0.685	0.842
Anti-PC Attitudes	3	0.861	0.992

We begin our investigation by examining the simple bivariate relationships between the hypothesized predictors. Table 3 contains correlations between each, as well as with partisanship and ideology. Most of the correlations are quite large and statistically significant at the $p < 0.05$ level. The exception is with conspiracy thinking, which – consistent with previous literature (Uscinski, Klofstad and Atkinson 2016) – 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, ranging from 0.489 to 0.725.

(by 0.015). Second, this cutoff is, itself, trivial. The disciplinary norms of which it is born are not, to our knowledge, the product of empirical research into the "best" (average) cutoff value. Finally, other measures of reliability that perform better than Cronbach's alpha (i.e., are less sensitive to sample size, provide a closer estimate of true reliability), such as the greatest split half reliability or the greatest lower bound, exceed 0.70.

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

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Racial Resentment	1.000					
(2) Conspiracy Thinking	0.108*	1.000				
(3) Anti-Immigrant Attitudes	0.725*	0.115*	1.000			
(4) Sexism	0.635*	0.134*	0.596*	1.000		
(5) Anti-PC Attitudes	0.633*	0.214*	0.634*	0.514*	1.000	
(6) Partisanship	0.579*	0.029	0.586*	0.531*	0.489*	1.000
(7) Ideological Self-identification	0.642*	0.072	0.662*	0.612*	0.565*	0.680*

Cell entries are Pearson correlation coefficients.

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

From the magnitude of the intercorrelations in Table 3, one can already imagine the difficulties in disentangling the effects of each of these constructs on support for Trump (Achen 2002, Schrodt 2014). Multicollinearity will certainly affect substantive inferences by increasing standard errors, leading to inaccurate tests of statistical significance. Multicollinearity 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 theoretical and statistical issues of a different sort. Theoretically, models omitting too many variables will be misspecified and incapable of appropriately testing claims. Statistically, the omitted variable bias that would result from such a strategy would cause biased estimates of the effects of variables in the model. The likelihood of such a scenario increases as the magnitude of the intercorrelations between predictors increases.

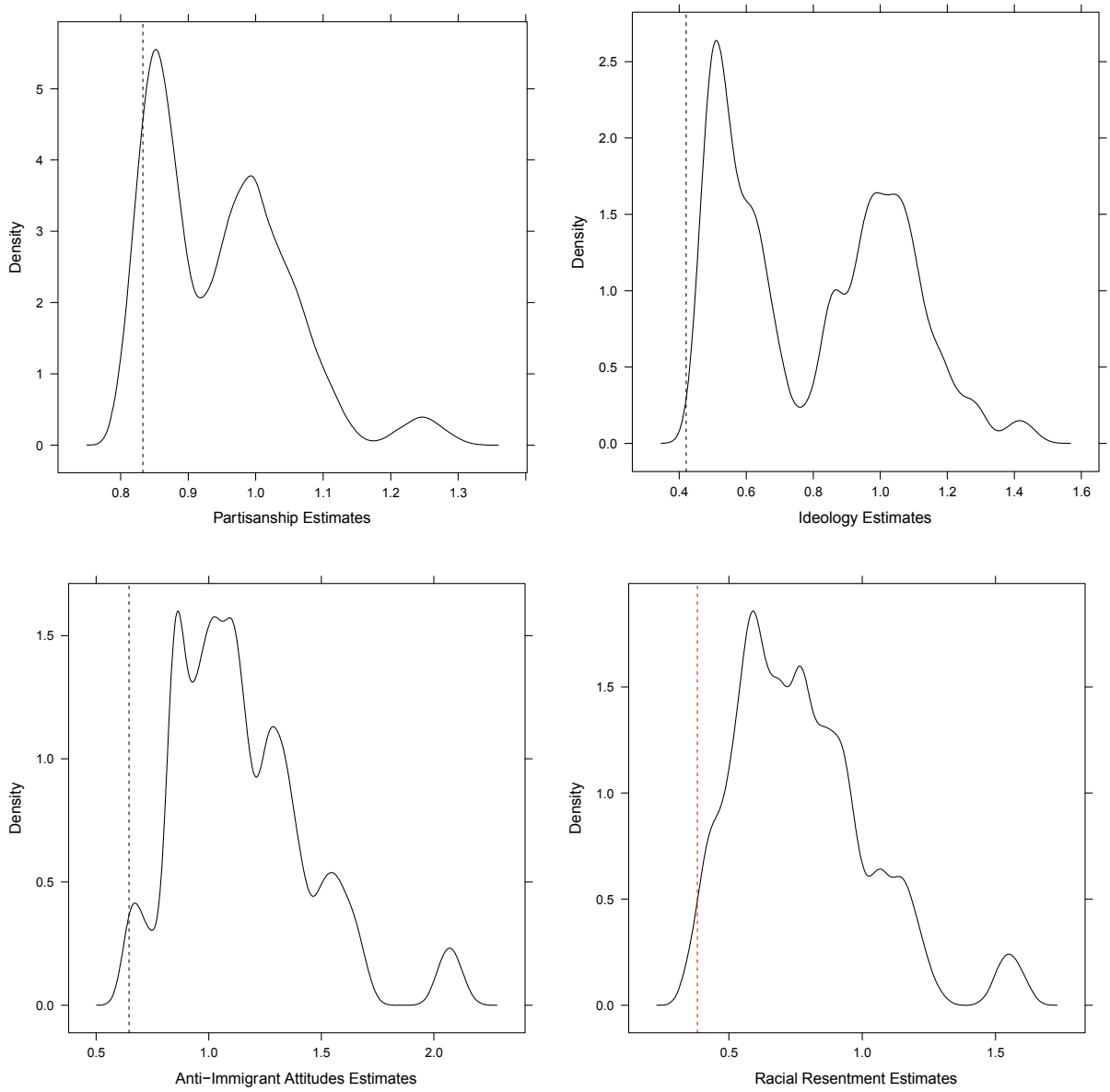
To determine a viable path forward, we first undertake a series of model robustness checks per the routine devised by Young (2009) and Young and Holsteen (2017). These checks are designed to reveal the stability of estimates across model specifications, providing some

empirical grasp on the potential effects of multicollinearity and omitted variable bias. First, we decide on core set of theoretical and control variables that should be included in our models of Trump support and voting. These include: partisanship, ideological self-identification, racial resentment, anti-immigrant attitudes, sexism, anti-political correctness attitudes, conspiracy thinking, income, educational attainment, age, attendance at 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, possible model specifications for a model predicting Trump vote choice. Next, retained estimates associated with a variable of interest are plotted via a kernel density estimate. This provides an empirical estimate of a variable's "modeling distribution" – a distribution where variability is attributed to different model specifications rather than sampling error, like a sampling distribution. Finally, we use characteristics of these distributions across independent variables to make inferences about the stability of estimated effects across model specifications.

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 also suggest that previous attempts to empirically investigate the predictors of Trump support may be inaccurate – or, at least, incomparable – unless all of such predictors are included in the model. In other words, piecemeal investigations of the effects of our variables of interest may be misleading if controls for other explanatory factors are excluded from models.

Figure 1 shows the empirical modeling distributions for each of the explanatory factors of interest in logistic regression models of Trump vote choice. There are some systematic characteristics of the set of distributions worth considering. First, very few of the empirical modeling distributions approach anything approximating normality. Most distributions are skewed, at least (e.g., racial resentment, sexism); some are even bimodal (e.g., conspiracy thinking, ideological self-identifications). Moreover, estimates from the full model – depicted by vertical dashed lines – rarely represent the average or median estimate (i.e., the center of the empirical sampling distributions). This signifies that multicollinearity is high, as are the effects of omitted variable bias – 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 (hence the red dashed line) in the full model, despite non-zero coefficients in the vast majority of models. Indeed, the full model estimate of the effects of racial resentment and political correctness attitudes fall toward the very low end of the empirical modeling distributions; the distribution for conspiracy thinking is actually bimodal about 0, signifying that some models reveal positive estimates, some negative.

Figure 1: Density plots of coefficient estimates from model robustness analyses. Density based on 32,768 models. Dashed lines represent estimate from full model with all controls. Lines presented in red signify a statistically non-significant estimate from the full model.


Density
Partisanship Estimates
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Ideology Estimates
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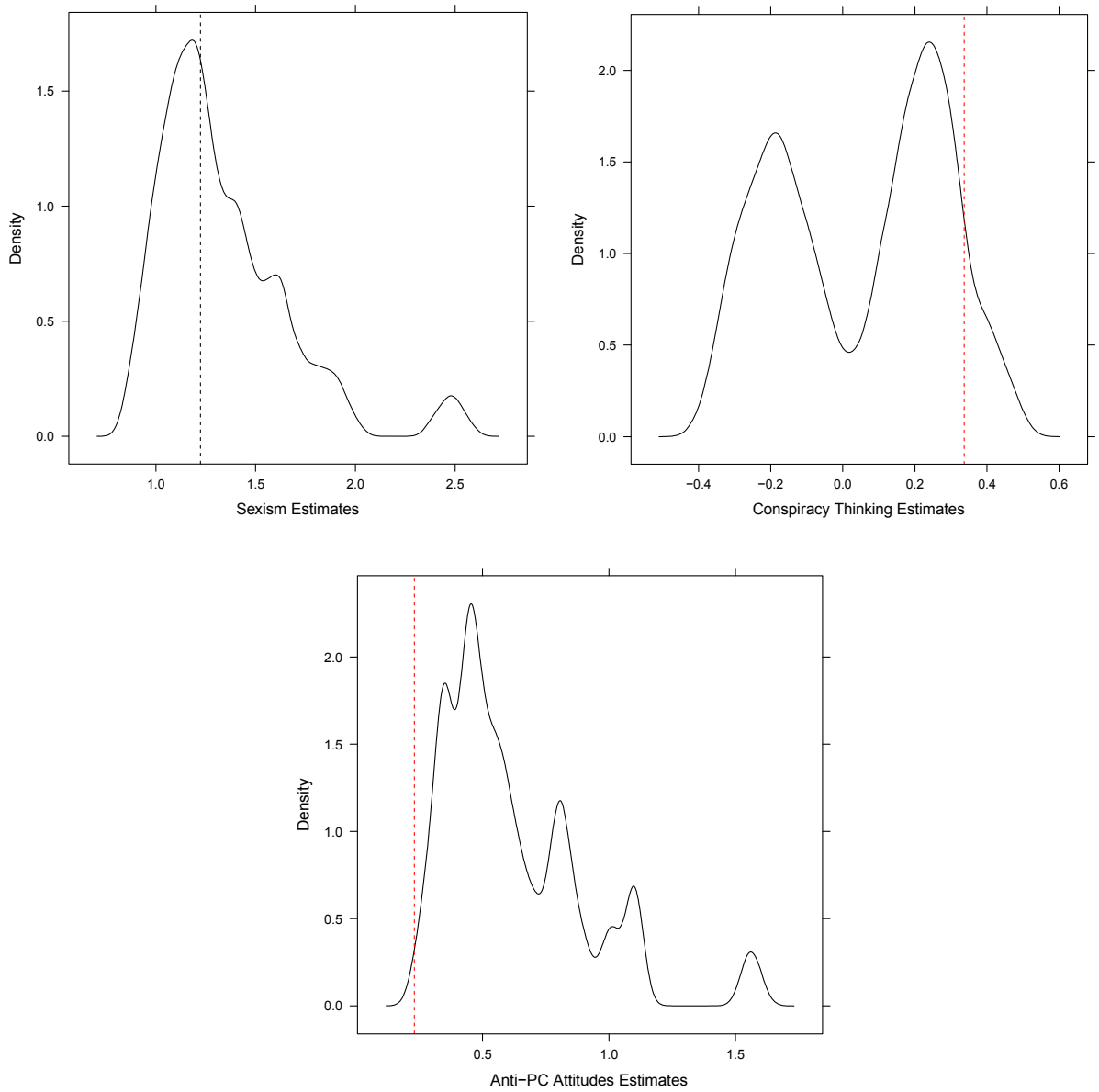
Anti−Immigrant Attitudes Estimates
Density
Racial Resentment Estimates



As noted above, 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 hypothesized predictors of Trump support are highly contingent on which of those predictors are included in the model. This may not seem like a particularly profound statement, *in practice*: Of course model estimates will change as the model

itself changes. But, this fact does not change the reality that previous attempts at understanding Trump support are simply incomplete because surveys do not typically include all of these factors.

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 reliable sign that Trump really did nothing to activate or foster racist, conspiratorial, or anti-change orientations. While conservative estimates are generally considered more desirable than the overestimations created by omitted variable bias, such conservative estimates also leave us unable to fully adjudicate between different reasonable, theoretically-informed accounts of the psychological foundations of Trump support.

Better Measurement: Creating a Profile

The solution to the remaining statistical problem lies in our understanding of the explanatory factors we are considering. Though researchers have pet explanations for Trump's popularity, few would dispute the interrelation between such explanatory factors. It makes good substantive sense that negative orientations toward racial groups, women, immigrants, political correctness, as well as conspiracy thinking are highly correlated – they are likely indicative of a broader cultural orientation characterized by perceived status threat, individual pieces of a larger profile of the average Trump supporter.

A reconceptualization – or formalization – of the individual explanatory factors associated with Trump support is both theoretically useful and empirically necessary. Conceptualization of a general orientation that underlies the various dimensions of support for Trump is more congruent with existing explanations of Trump support. It is also more parsimonious and does not require a majority of Trump supporters to be racists, anti-immigrant, or sexist to find empirical support. That is, this conceptualization allows individuals to have a profile along these individual factors, but circumvents the issue of branding all Trump supporters with uncharitable labels that may not be accurate. Empirically, a reconceptualization of Trump support along these lines circumvents some of the statistical problems associated with multicollinearity, resulting in a simpler – and, hopefully, more powerful – model of Trump support.

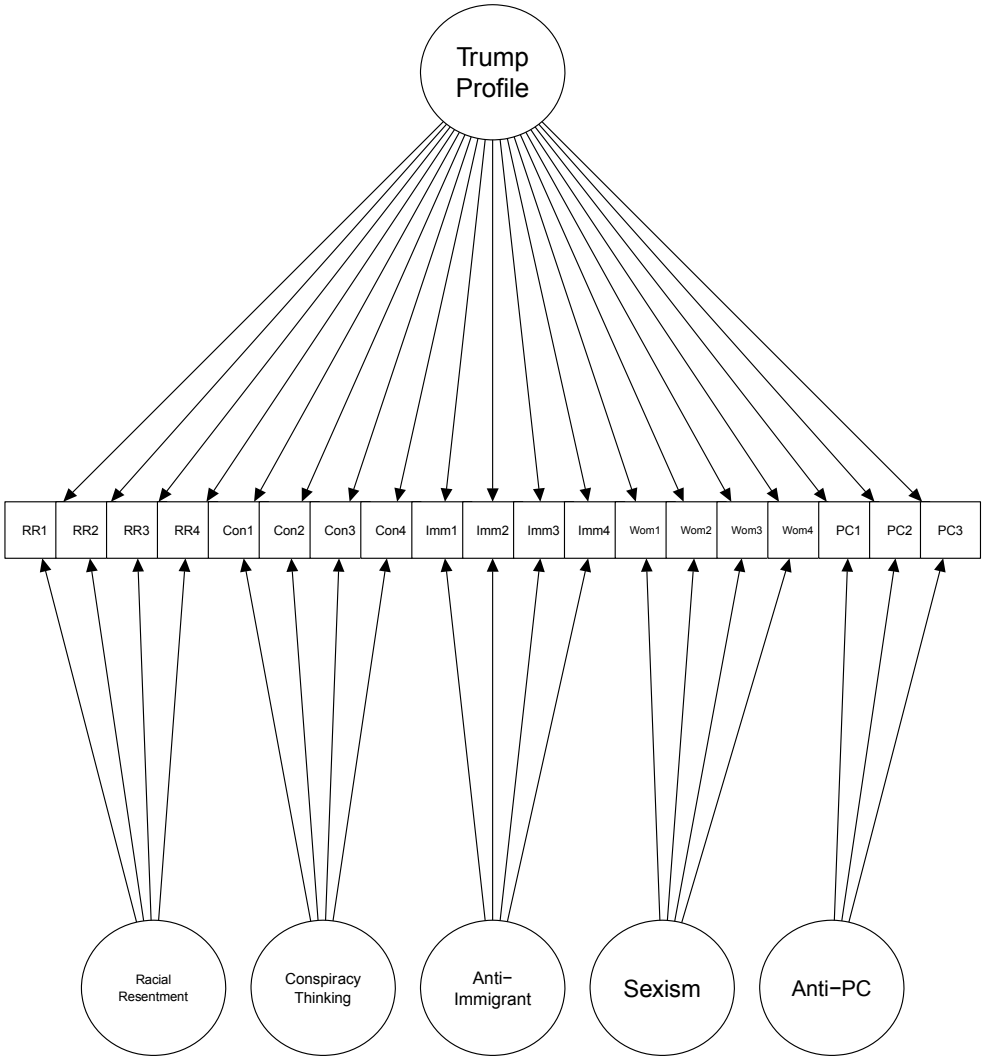
To understand the utility of this strategy, consider the example of intelligence. Intelligence researchers going back to Charles Spearman – perhaps the most influential figure in the development of the common factor model (Horn and McArdle 2007) – have posited that intelligence is both theoretically and empirically composed of a general intelligence factor, usually denoted "g," and many more individual factors that capture specific dimensions of intelligence, such as arithmetic ability, vocabulary, and visual perception. Modeling intelligence in this way allows individuals to vary along specific dimensions of intelligence, while still allowing individuals to be oriented along a single, general intelligence continuum.

This is precisely what we aim to do in modeling the variables associated with Trump support. We employ a bifactor model of the covariances between the observed indicators of racial resentment, anti-immigrant attitudes, sexism, conspiracy thinking, and anti-political

correctness attitudes. A path diagram of the bifactor model we estimate appears in Figure 2.[2] Here, the specific explanatory factors related to Trump support are analogous to the specific dimensions of intelligence, and a general "profile" – a broader cultural orientation – is analogous to the general intelligence factor. Observed covariances of the individual indicators of racial resentment, anti-immigrant attitudes, sexism, conspiracy thinking, and anti-political correctness attitudes are, theoretically, the causal product of both specific constructs of the same name and a more general orientation, what we call the "Trump profile." 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 – per the model robustness analyses presented above – consequential multicollinearity between predictors of Trump support.

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.

[2] A related, "higher-order model" operationalizes the general factor as causing the specific factors, and the specific factors, in turn, causing observed indicators. As is frequently the case, (Cucina and Byle 2017), this model does not fit the data quite as well, though the substantive results tend to be very similar. For instance, the correlation between the predicted general factor scores are highly correlated at 0.99. Ultimately, we do not believe that the effects of the general factor should be moderated by the specific factors, which is the theoretical relationship implied by the higher-order model. Indeed, the utility of our reconceptualization of Trump support, and the bifactor model that operationalizes it, is that many of the specific indicator items may be less related to racial prejudice or sexism than a general dismay for changing cultural norms and perceived status threat. This is a thin line, but an important distinction nonetheless.



Estimates from the bifactor model are reported in Table 4.[3] 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, and all observed indicators significantly load on the general Trump profile factor. Moreover, all fit statistics suggest excellent model fit. The root mean squared error of approximation (RMSEA) is at the recommended 0.05 cutoff for

[3] We used the "lavaan" package in R to estimate the model. The "mirt" package, which is capable of estimating the bifactor model under the IRT parameterization, provides identical substantive inferences.

“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). It appears that the relationships between specific explanations for Trump support can be accurately accounted for using the bifactor structure – a structure where a single, common orientation influences a wide array of specific attitudes.

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

	General	Racial Resentment	Conspiracy Thinking	Anti-Immigrant Attitudes	Sexism	Anti-PC Attitudes
Racial Resentment						
RR1	0.785*	0.382*				
RR2	0.757*	0.423*				
RR3	0.747*	0.398*				
RR4 .	0.767*	0.339*				
Conspiracy Thinking						
Con1	0.280*		0.738*			
Con2	0.095*		0.488*			
Con3	0.121*		0.586*			
Con4	0.143*		0.840*			
Anti-Immigrant Attitudes						
Imm1	0.708*			0.206*		
Imm2	0.727*			0.227*		
Imm3	0.840*			0.394*		
Imm4	0.748*			0.344*		
Sexism						
Wom1	0.349*				0.555*	
Wom2	0.791*				0.117*	
Wom3	0.422*				0.322*	
Wom4	0.679*				0.101	
Anti-PC Attitudes						
PC1	0.739*					0.406*
PC2	0.800*					0.442*
PC3	0.600*					0.472*
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			

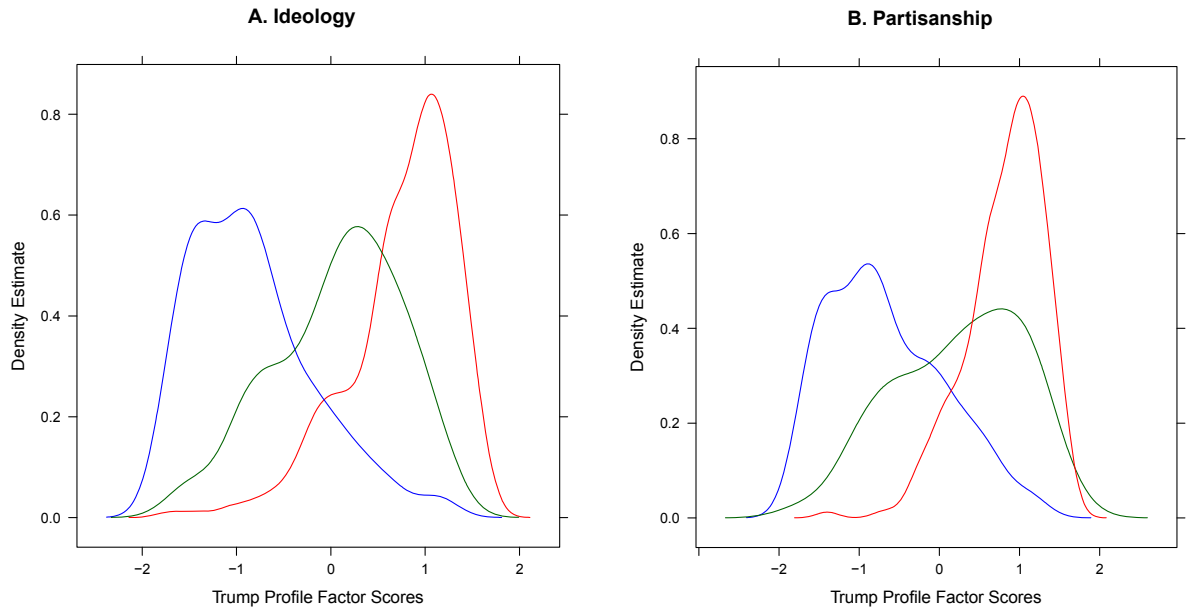
Standardized MLE coefficients. * $p < 0.05$ level with respect to a two-tailed test.

Basic reliability and construct validity established, we next consider concurrent validity – the extent to which the predicted Trump profile factor is capable of distinguishing between groups it should theoretically be able to distinguish between. We consider the distribution of Trump profile factor scores by partisanship and ideology, presented in Figure 3. In both cases we observe fairly distinct bimodal distributions with Republicans and conservatives clustered to the

high end of the scale, and Democrats and liberals toward the low end. “Pure” independents and moderates are widely distributed across the range of the Trump profile, with slightly more clustered toward the top end of the scale.

The findings in Figure 3 provide precisely what we would expect. On the one hand, the attitudes that compose the Trump profile should discriminate between partisan and ideological identities, *to some extent*. On the other hand, it is clear from the figure that a non-trivial proportion of conservatives and Republicans are low on the Trump profile, while a non-trivial proportion of liberals and Democrats are high or middling on the Trump profile. And, moderates and independents are oriented at all locations on the latent continuum. Thus, the Trump profile is related to partisanship and ideology, but far from determinative of them. That said, if elections are increasingly won on the margins, the partisan and ideological distributions of the Trump profile strike us as being fairly congruent with the cross-national results from the 2016 presidential election – even a small amount of partisan and ideological overlap in the center of the Trump profile means the election is fair game for any candidate.

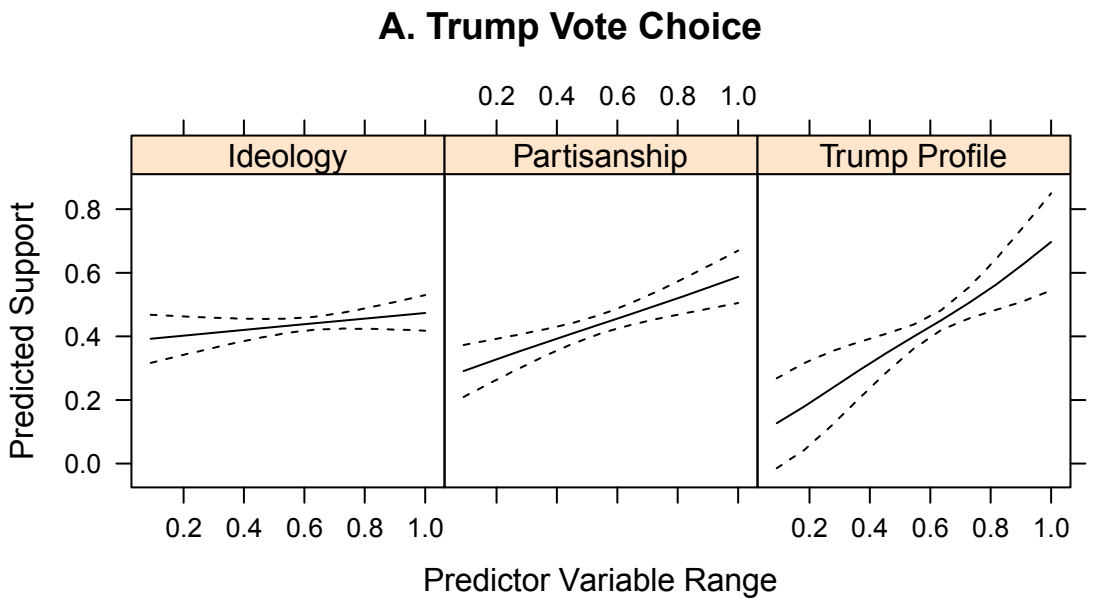
Figure 3: Distribution of the Trump Profile factor, by self-identification as a liberal/Democrat (blue), conservative/Republican (red), or moderate/independent (green).

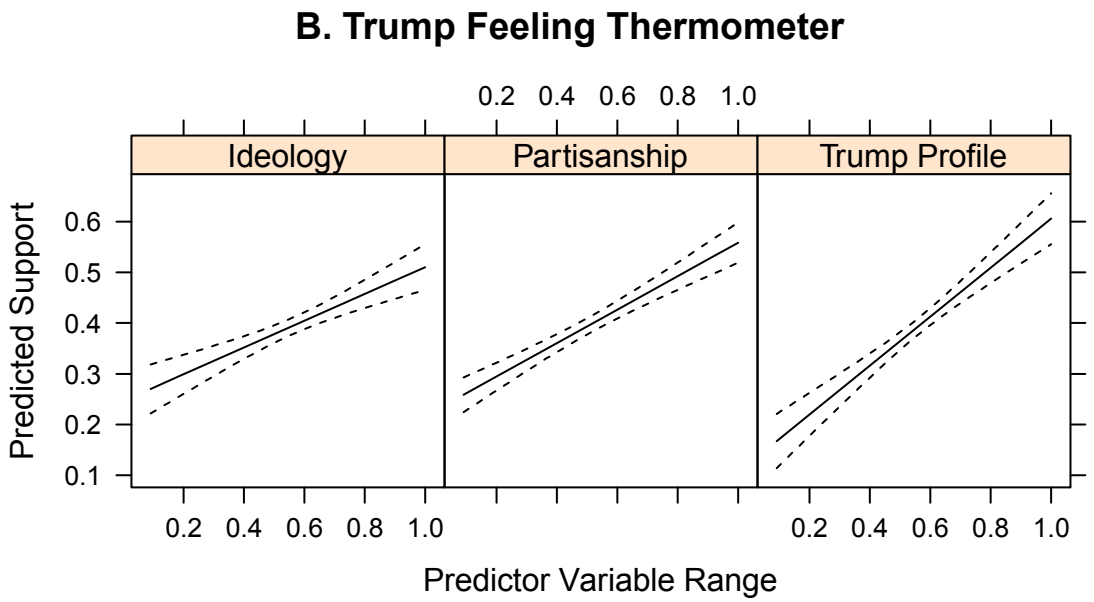


Predicting Support for Trump and Related Sentiments

The penultimate stage of our investigation entails demonstrating the predictive power of the Trump profile. We do so with respect to both specific measures of Trump support (e.g., feelings toward Trump, voting for Trump) and a set of issues regularly promoted by Trump: climate change denial, skepticism about Trump collusion with Russia, and distrust of the news media. Strong and statistically 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 posited explanations for Trump support as indicative of a single, broader cultural sentiment.

Figure 4: 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. Interval and ordinal control variables held at their mean, nominal at modal value. Dashed lines represent 95% confidence intervals.





First, we regressed Donald Trump feeling thermometer scores (0-100) and (retrospective) Trump vote choice on the Trump profile, as well as partisanship, ideology, and host of controls for retrospective evaluations of the national economy, income, religiosity, educational attainment, age, race/ethnicity, gender, and residence in the South.[4] Ideology, partisanship, and

[4] All variables were rescaled to range from 0 to 1.

the Trump profile are all coded such that larger values denote more conservative, Republican, and Trump-sympathetic orientations. Full model results appear in the Supplemental Appendix, but model-based predictions over the range of the three explanatory variables of interest appear in Figure 4.[5]

The coefficients on the explanatory variables of interest are statistically significant, and they are larger than any of the other control variables in the model, such as 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 variable. This is easily ascertained via inspection of the slopes of the model predictions in Figure 4. Take, for instance, the predicted probability of a vote for Trump over Clinton or another candidate in panel A of Figure 4. 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.

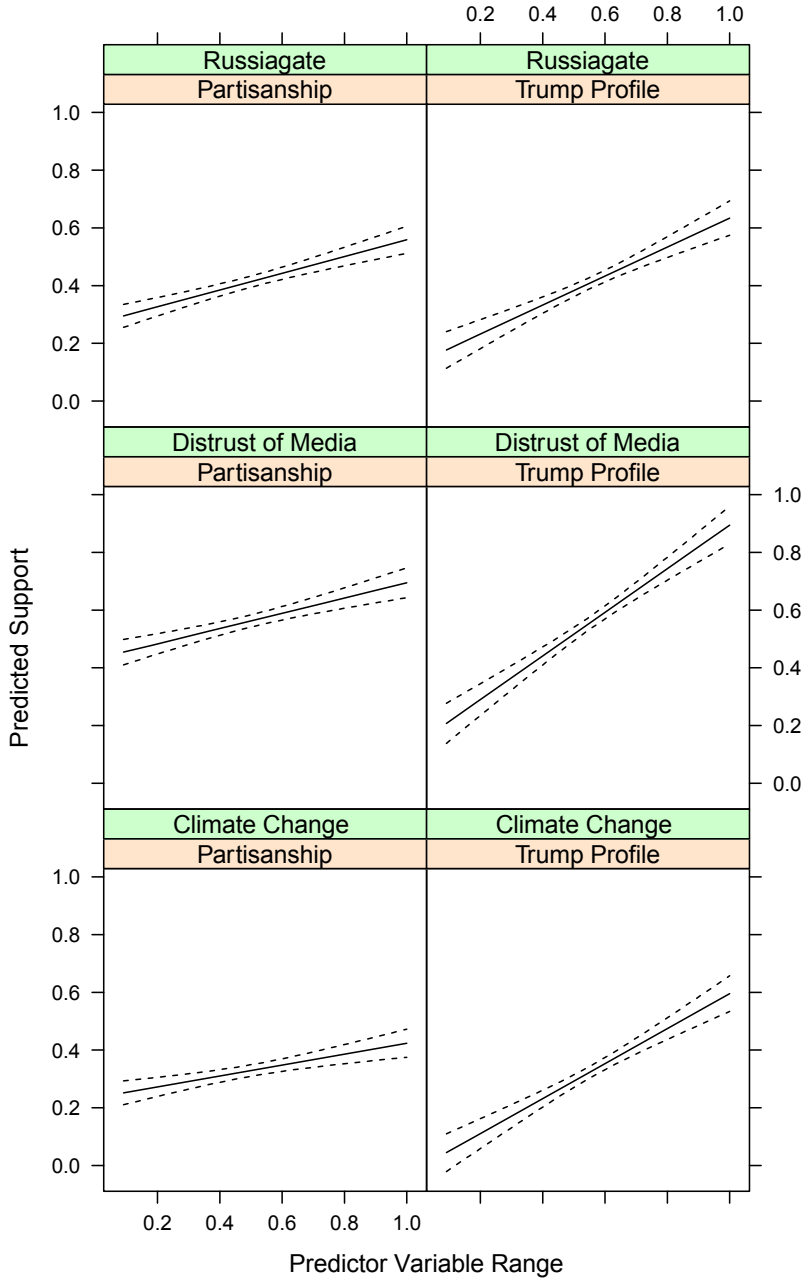
Moreover, the Trump profile variable provides a significantly better model fit in both instances. The change in R^2 from the naïve Trump feeling thermometer model without the Trump profile variable to one with the Trump profile is 0.09. The same for the vote choice model (pseudo- R^2) is 0.05. Although these may not seem like large changes in predictive power, both full models have R^2 values over 0.75, which is quite high for survey data. And, any significant predictive power beyond the domineering effects of partisanship and ideology is worthy of

[5] 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.

serious consideration. Finally, the models including the Trump profile variable are statistically better (i.e., larger R^2) than the more complicated models including each of the individual explanatory factors as independent variables. In other words, models including the Trump profile are better than any other model theory may lead one to estimate.

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. Once again, all variables were rescaled 0 to 1, where larger values denote Trump-congruent positions. Full model estimates appear in the Supplemental Appendix, and model predictions over the range of the Trump profile and partisanship appear in Figure 5.

Figure 5: 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. Interval and ordinal control variables held at their mean, nominal at modal value. 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 very low on the Trump profile variable 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 are precisely the opposite. The Trump profile is also more predictive of these attitudes than are either partisanship (pictured) or ideological self-identifications. These analyses demonstrate how powerful and all-encompassing the general cultural orientation that defines the Trump profile is to myriad political attitudes, especially when this cultural orientation is cued, fostered, and redirected by a media-savvy politician.

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 above analyses using the 2016 ANES, which included many of the variables utilized above. Of those, most are either direct replications or substantively identical (question wordings in Supplemental Appendix). We note that the 2016 ANES included a battery of items designed to measure authoritarianism, an oft-cited reason for Trump support (e.g. MacWilliams 2016b) that was not available on the 2018 CCES. Unfortunately, however, the 2016 ANES does not include measures of conspiracy thinking,[6] and only includes a single measure of attitudes toward political correctness. Theoretically, this should result in a less complete account of Trump support. Statistically, this may result in a blunter measure of the Trump profile, though we are able to include a new construct – authoritarianism.

We expect similar results using the 2016 ANES precisely because the profile approach should be robust to relatively minor alterations in the specific attitudinal items included in the model if our theory about a broader cultural orientation underwriting such attitudes holds weight.

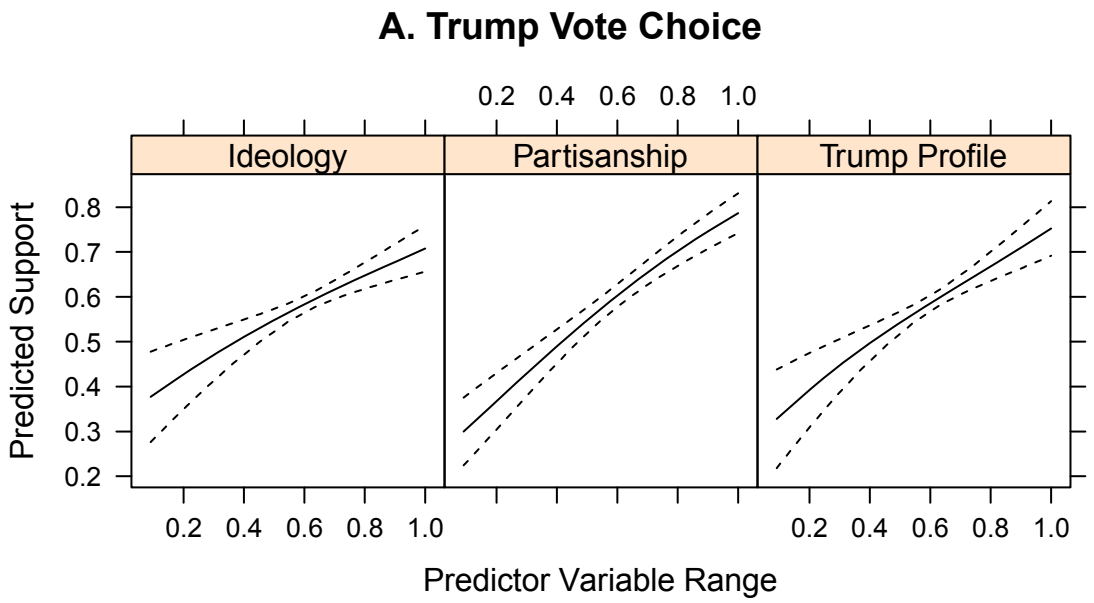
[6] No questions on the 2016 ANES measured general conspiracy thinking. The specific conspiracy belief items included are problematic as measures of general conspiracy thinking (Enders, Smallpage and Lupton 2018).

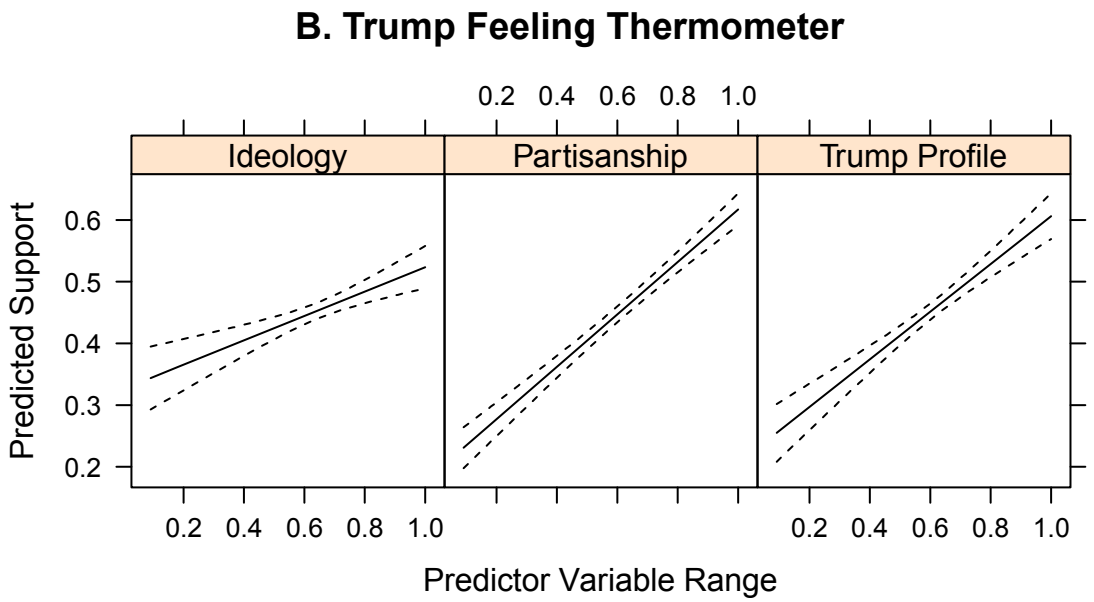
Moreover, the 2016 ANES dataset includes measures of attitudes about other issues that Trump has seemingly claimed ownership over (e.g., "the wall," and anti-vaxx attitudes), as well as self-reported Republican primary voting. The latter information is particularly useful in establishing that the Trump profile is, indeed, specific to Trump and not merely a substitute for more traditional conservative ideological principles or "mainstream" Republicanism.

Despite altogether missing indicators for conspiracy thinking, and less indicators of attitudes toward immigrants and political correctness, the bifactor model fits the data well.[7] 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 factor scores and measures of support for Trump and Trump-related issues. Figure 6 depicts the relative influence of partisan and ideological self-identifications and the Trump profile on feelings toward Trump and Trump vote choice in the general election. Although the effects of the Trump profile and partisanship are slightly more comparable than we observed in the 2018 CCES data, the effects of the Trump profile rival those of partisanship and prove greater than those of ideology. These very minor discrepancies could be attributed to data that is more proximal to the 2016 election, or they could be due to an incomplete estimate of the Trump profile. Either way, our empirical estimate of the Trump profile is substantively very similar to that found using the 2018 CCES data, underscoring the utility of the analytical strategy.

Figure 6: 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. Interval and ordinal control variables held at their mean, nominal at modal value. Dashed lines represent 95% confidence intervals. 2016 ANES data.

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

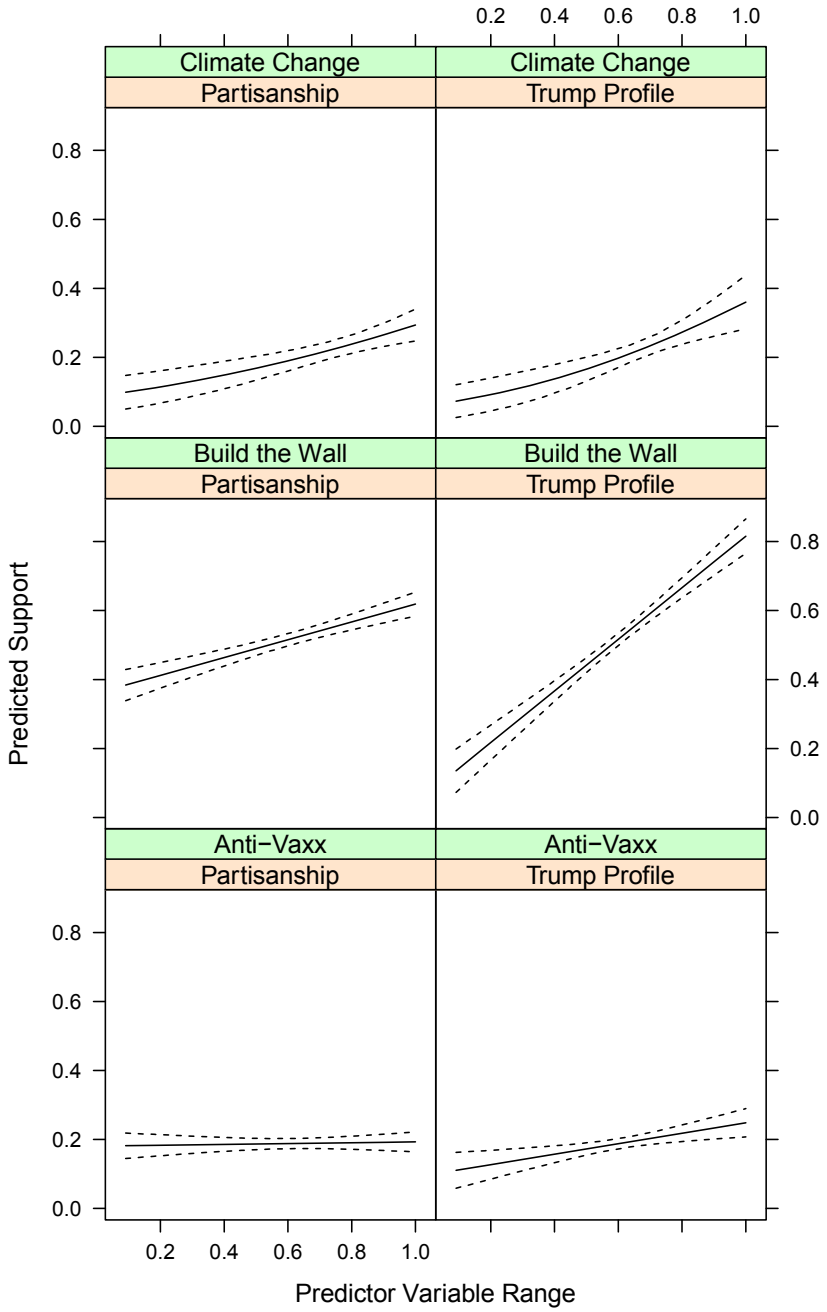




We also find that the Trump profile is highly predictive of attitudes about Trump-related issues. Figure 7 depicts the influence of the Trump profile and partisanship on skepticism of climate change and vaccines, and on attitudes toward the U.S.-Mexican border wall, holding other factors like ideology and socio-demographic characteristics constant. As before, we observe substantively large effects of the Trump profile in accounting for attitudes about the

issues that Trump is widely associated with. 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 anti-vaxx attitudes, the latter of which does not have a statistically significant relationship with partisanship or ideology.

Figure 7: 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. Interval and ordinal control variables held at their mean, nominal at modal value. Dashed lines represent 95% confidence intervals. 2016 ANES data.



Finally, we consider the discriminatory power of the Trump profile. If this cultural orientation that we have captured is truly indicative of Trump support more so than conservatism or Republicanism, it should predict support for Trump over other Republican candidates, controlling for partisanship, ideology, and other known predictors. This is precisely what we

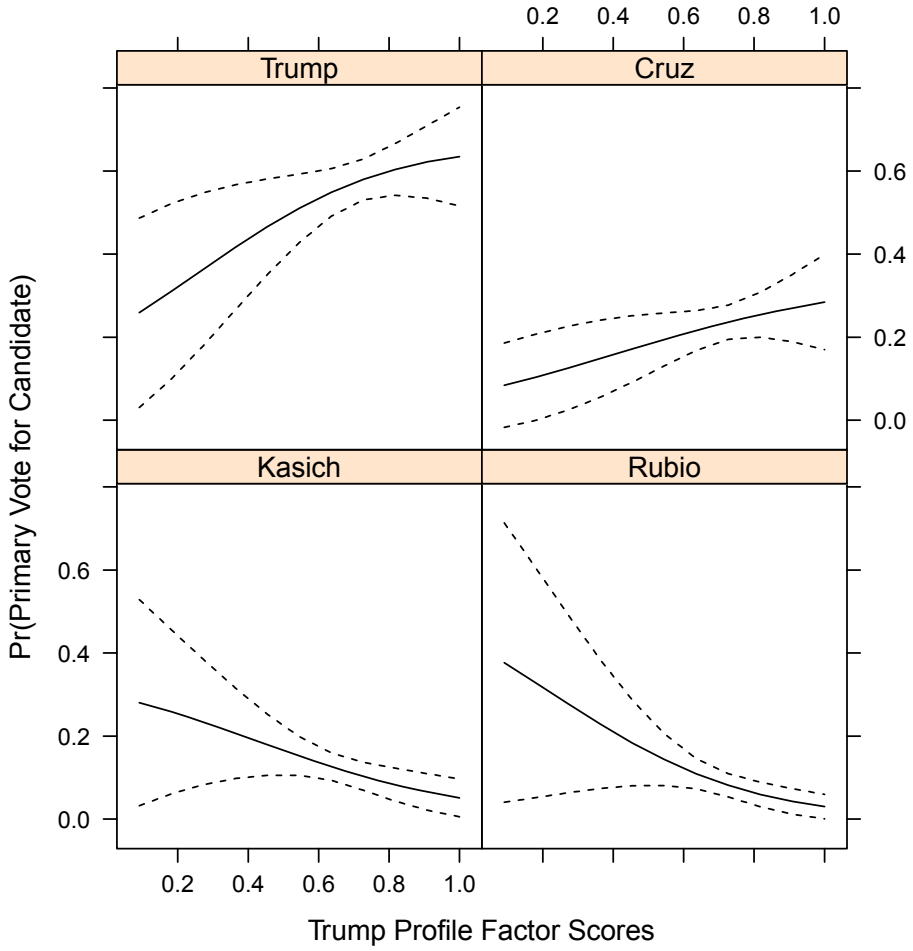
find. We estimate a multinomial logistic regression where the dependent variable captures voting for Trump, Ted Cruz, John Kasich, or Marco Rubio in the 2016 primary elections. The predicted probability of casting a vote for each of the candidates across the range of the Trump profile, holding constant the strength of partisanship and ideology, retrospective evaluations of the economy, and socio-demographic characteristics, is depicted in Figure 8.[8]

Even among self-identified Republicans voting in the primary, the Trump profile exhibits a great deal of predictive power in explaining support for Trump.[9] We find a weak positive relationship between the Trump profile and voting for Cruz, as we might expect given some of the similarities between the candidates' platforms and campaign strategies. Such is not the case when it comes to mainstream candidates Rubio and Kashich. For both of these mainstream Republican candidates, we observe a negative relationship between the Trump profile and candidate support.

Figure 8: Predicted probability of voting for each of four Republican candidates in the 2016 U.S. presidential primaries, controlling for other factors. Respondents are Republicans. Interval and ordinal control variables held at their mean, nominal at modal value. Dashed lines represent 95% confidence intervals. 2016 ANES data.

[8] Full model estimates appear in the Supplemental Appendix.

[9] 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). Some Republicans of average conservative ideology that are low on the Trump profile still may have voted for Trump, just as they may have voted for Kasich or Rubio.



In sum, the Trump profile appears to be predictive of not only feelings about Trump and the unique issues attached to him, but even support for other Republican candidates, albeit in a different direction. Moreover, models including the Trump profile, rather than scales of the individual attitudes that compose the Trump profile, perform better than other modeling strategies. In Table 5, we present AIC and BIC estimates for three models 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 factors such as religiosity, race and ethnicity, educational attainment, income, gender, and residence in the South. Taking this as a base model of sorts, we

also specify models that add all individual orientation scales ("Traditional + Individual Scales") or that simply add the Trump profile ("Traditional + Trump Profile"). Small model AIC and BIC estimates indicate better model fit – a combination of predictive power and parsimony (i.e., number of parameters estimated).

AIC and BIC disagree about whether the Trump profile model is better than the individual scale model for affect toward Trump in the 2018 CCES data and Trump vote choice in the 2016 ANES data. For the other two dependent variables, the Trump profile model performs best according to the AIC and BIC. Thus, we possess supportive evidence that Trump profile performs well, 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 AIC and BIC fit statistics for traditional vote choice models, traditional models plus individual predictors or Trump support, and traditional model plus Trump profile.

	AIC	BIC
Trump Thermometer, 2018 CCES		
Traditional Model	-185.4956	-124.8915
Traditional + Individual Scales	-290.6149	-208.3895
Traditional + Trump Profile	-271.8871	-212.0669
Trump Vote Choice, 2018 CCES		
Traditional Model	225.3695	281.9763
Traditional + Individual Scales	190.8178	268.3308
Traditional + Trump Profile	179.3076	239.1279
Trump Thermometer, 2016 ANES		
Traditional Model	-61.88544	6.664764
Traditional + Individual Scales	-240.5562	-145.6906
Traditional + Trump Profile	-269.5036	-199.7176
Trump Vote Choice, 2019 ANES		
Traditional Model	459.5054	524.8026
Traditional + Individual Scales	393.1022	483.4656
Traditional + Trump Profile	393.5545	463.3405

A Cautionary Note on Interpretation

So far, we have claimed that the many posited sources of Trump support can be woven together by perceived status threat and a worry over changing moral and social values, a perspective that has gained a great deal of traction in the past few years (e.g., Jardina 2019, Mutz 2018a). It is precisely this theory that we use to justify creation of the Trump profile – the core of our modeling strategy. We end our empirical investigation with a cautionary note about the interpretation of survey questions from this theoretical perspective.

It strikes us that perceived status threat is quite different in psychological nature than racial prejudice or sexism. The former is a passive, subconscious expression of fear, and a desire for self-preservation. The latter, however, are more active in nature. This is how we tend to think about the "isms," especially as they pertain to a divisive and outspoken world leader such as Donald Trump. If, however, our theory about perceived status threat is to be taken seriously, then substantive interpretation of the Trump profile – beyond an examination of predictive power – should be taken equally seriously. As an illustration of what exactly variation along the Trump profile means – or could mean – consider the individual attitudinal profiles presented in Table 6. We randomly sampled two individuals from the 2018 CCES dataset: one at, or lower that, the 25th percentile along the 0-1 Trump profile, one at or higher than the 75th percentile. The goal was to randomly acquire relatively extreme individuals in both directions, so that their individual attitudinal profiles may be examined.

Table 6: Examples of individual attitudinal profiles for relatively high and low values on the Trump profile factor.

	Trump Profile Scores (0–1)	
	0.29	0.74
Symbolic Political Predispositions		
1) Partisanship	Strong Democrat	Lean Republican
2) Ideology	Extremely Liberal	Slightly Conservative
Racial Resentment		
1) Generations of slavery and discrimination have have created conditions that make it difficult...	A	D
2) It's really a matter of some people not trying hard enough	SD	A
3) Over the past few years, blacks have gotten less than they deserve.	D	SD
4) Irish, Italian, Jewish, and many other minorities overcame prejudice and worked their way up...	D	A
Conspiracy Thinking		
1) Much of our lives are being controlled by plots hatched in secret places.	A	N/N
2) Even though we live in a democracy, a few people will always run things anyway.	A	A
3) The people who really 'run' the country are not known to the voters.	A	N/N
4) Big events like...outcomes of elections are controlled by small groups of people...	D	N/N
Anti-Immigrant Attitudes		
1) Illegal immigrants increase crime in the US.	D	A
2) Illegal immigrants decrease wages for Americans.	D	N/N
3) Immigrants contribute more in taxes than they receive in health and welfare services.	N/N	D
4) Immigration in general should be slowed down.	N/N	SA
Sexism		
1) Women should earn the same wages as their male counterpart.	SA	A
2) A woman's place is in the home.	D	SD
3) The news media have been showing more concern about...women than is warranted...	D	N/N
4) Feminists are making entirely reasonable demands of men.	D	A

Note: SA="strongly agree," A="agree," N/N="neither/nor," D="disagree," SD="strongly disagree"
Case identification numbers: 416172031, 416179346

The first individual sampled scored a 0.29 on the Trump profile. They registered as a strong Democrat and extremely liberal – the most extreme positions on the two most important political orientation measures in political science. The second individual, who registered as a Republican Party "leaner" and slightly conservative, scored a 0.74. Despite a wide gap on the

Trump profile and scores in the first and fourth quartile, neither respondent provides particularly extreme responses in either direction. Of the three extreme responses provided by the conservative respondent, one deals with "deservingness" of blacks, another with a rather tame attitude about immigration being "slowed down," and a third – strong disagreement that a woman's place is "in the home" – that is very liberal. Indeed, this respondent is more supportive of equal rights for women and less conspiratorial than the more liberal respondent who is low on the Trump profile.

Our point is that neither the strong correlation between the Trump profile and other attitudes, nor the construct validity of the Trump profile, should be taken as evidence that all Trump supporters are racist, sexist, xenophobic, conspiracy theorists. Indeed, a small proportion of respondents are consistently extreme in the uncharitable direction, and no more than 8.5 percent of respondents are extremely negative across all survey questions composing each of the anti-immigration, racial resentment, conspiracy thinking, or sexism scales. Further, no one in our sample is consistently extreme across all orientations. While it is true that our Trump profile predicts Trump support as well as or better than partisan identification, our strategy highlights nuance to the substantive interpretation of the *levels* of these attitudes, as well as their *associations* with other things like Trump support.

Conclusion

Numerous factors, such as attitudes towards race, and variations of those factors (e.g., racial resentment, white group identity) have been shown to predict Trump support, and in some ways the scientific enterprise of explaining the Trump phenomenon has become a game of one-upmanship where scholars continually identify a "new" factor that is a statistically significant

predictor of Trump support. In this manuscript, we highlight the value of the extant literature, but also point out its limitations. We sought to provide a comprehensive investigation of the many posited sources of support for Donald Trump in the 2016 U.S. presidential election. Many of these psychological sources of support – racial prejudice, sexism, conspiracy thinking, anti-political correctness – have been operating in American politics long before 2016 and have been since. As such, the analyses presented above are useful for our understanding of the American political landscape well beyond the confines of the Trump years, and also suggestive of psychological and identity-based processes operating in other political contexts, such as support for authoritarian politicians in Europe and the "Brexit" movement in the United Kingdom.

Using unique data to measure many of the hypothesized predictors of Trump support with multiple indicators of each, we demonstrate that such predictors are highly correlated. Our model robustness analyses reveal highly unstable estimates of important predictors with respect to magnitude, sign, and statistical significance. The multicollinearity between variables caused substantial omitted variable bias over the range of possible models that left certain factors out.

In order to address the multicollinearity, while both circumventing the negative effects of omitted variable bias and adhering to theory, we specified a bifactor model that combined observed indicators of the hypothesized predictors of Trump support. The general factor resulting from this modeling strategy – what we call the Trump profile – is highly predictive of voting and support for Trump, even controlling for partisanship, ideology, and other factors. Moreover, it is uniquely predictive of support for Trump-owned issues, as evidenced by its relationship with attitudes about building "the wall," childhood vaccinations, distrust of the media, and climate change denialism. The Trump profile, however, does not measure Republicanism or conservatism in another way: it is negatively associated with support for other

Republican candidates in the 2016 primary elections. In short, a profile composed of attitudes towards racial groups, women, immigrants, PC culture, and conspiracies/elites can better explain support for Trump and his espoused policies than the traditional predictors of partisanship and ideology.

Our approach is useful for several reasons. First, it obviates the necessity of scholars to accept the consequences of either multicollinearity or omitted variable bias in their models of vote choice. Indeed, our strategy largely circumvents the negative effects of these statistical phenomena. Second, our strategy is simply more congruent with theories of Trump support – it models the individual constructs as the product of both specific factors and more a general factor that captures the cultural orientation Trump was said to successfully cue. In other words, the bifactor modeling strategy allows both the inclusion of a majority of the posited predictors of Trump support, thereby avoiding statistical issues, as well as providing a better measure of the factors that explain Trump support than any one of, or even a large subset of, those factors alone.

Despite the high correlation between the Trump profile and partisan and ideological self-identifications, it is clear that the measure is not a mere substitute for such symbolic political orientations. Partisanship and ideology remain highly predictive of Trump support controlling for the Trump profile, not to mention the rather obvious fact that not all Republicans or conservatives exhibit obviously racist or sexist orientations. As other scholars have begun to show, Trump supporters are different than non-Trump supporting Republicans (Barber and Pope 2019, Blum and Parker 2019). The bifactor modeling strategy generates a cultural orientation that is a mix of more specific attitudes that are correlated with the left-right political dimension, and those that are not (or only weakly so). By capturing a broader cultural orientation toward

low-status groups, power structures, and aversion to cultural change, we were able to more powerfully model the sentiment at the heart of Trump support.

We reiterate our caution about the exact nature of Trump support. Our final analysis, examining the actual responses to individual survey questions, reveals that very few individuals, even on the high end of the Trump profile, provide extreme attitudes about racial minorities, women, immigrants, or elite conspiratorial activities. And even if that were the case, extreme responses to many of the survey items used to measure concepts like racism or "hostile" sexism (including our own, see Supplemental Appendix), would not *necessarily* qualify one as a racist or misogynist as commonly understood. For example, being in strong agreement that "feminists are making entirely unreasonable demands" says little about misogyny or one's views toward equality. This is in addition to the obvious points that not all respondents interact with the survey items in the same way, and that substantive interpretations should be made carefully.

By our reading of the specific attitudinal profiles of respondents, Trump support could be accounted for by a perceived threat to some peoples' status in society, or perhaps even a more general fear of changing societal values and traditions. In other words, individuals might exhibit attitudes that *could be interpreted* as racist, sexist, xenophobic, etc., but which, in actuality, are not born of a deep, antagonistic relationship with minorities or women. Status threat and traditional values do not require a hatred of others, only a sense and fear that things are changing in ways that are difficult to come to grips with. People are innately view the past with rosy hindsight, have a fear of change. This longing nostalgia may very well be expressed in ways that are unseemly, and can be harnessed by politicians (Gaston 2018). Consider the longing for a time when more products were made in the US by Americans; this rather benign view could easily be connected to anti-trade and anti-immigration attitudes by a strategic politician.

So, we are left with a choice: the charitable or the uncharitable interpretation. Of course, the decision should not reflect our relative willingness to be "nice" in our assessment of people. Rather, it should be based in scientific values, such as parsimony, made in conjunction with other relevant information, as well as an understanding of the potential consequences of our inferences. Despite losing the popular vote, Trump received almost 63 million votes. To label all of these individuals as racist, sexist, xenophobic conspiracy theorists is a serious charge – one that researchers should be hesitant to make. Incorrect inferences have the potential to erode academic authority and inflame the negative orientations researchers are attempting to analyze.

The "ism" labels also strike us as less parsimonious, to an extent. Indeed, to charge nearly half of the country with being racist, sexist, and xenophobic, all the while many of such individuals claim that economic security and safety are the prime motivating factors for vote choice, is complicated and elitist. Our modeling strategy provides a way forward for reinterpreting observed attitudes in a way that is more cautious, more compatible with self-reports from the people we study, and more congruent with scientific principles of inquiry.

This is not to dismiss the normatively problematic consequences of the ingredients of the Trump profile. Some of Trump's supporters do indeed exhibit attitudes and behaviors born of a deep-seated antagonism with minorities and women. Further, attitudes positively related to support for authoritarian politics and white ethno-nationalism pose a serious challenge to a civilized democratic politics (Bonikowski 2017, Maskovsky 2017, Whitehead, Perry and Baker 2018), however we interpret such attitudes. Rather than provide a definitive accounting of the psychological sources of support for Trump, we hope that our findings cause researchers to be more circumspect in the substantive inferences they make from survey responses, consider alternative strategies for measuring racial prejudice, sexism, xenophobia, and the like, and be

cognizant of implicit biases that may impose on the scientific process (al Gharbi 2018, Reicher and Haslam 2017, Zigerell 2019). For example, scholars across disciplines pathologized conspiracy theorists for most of 21st century (Butter and Knight 2018, Hofstadter 1964). Only upon recent re-inspection have they come to see conspiracy beliefs as the product of common psychological, political, and social biases that everyone falls victim to from time to time (Douglas, et al. 2019). Researchers should not make the same mistake with respect to supporters of any one political candidate or party.

Facing a crowded primary field, it was entrepreneurial for Trump to activate attitudes that other candidates were not (Ashbee 2017, Reicher and Haslam 2017); he clearly benefited from it. Will this strategy work in 2020? Analysts are currently mixed on this point because his rhetoric also repels those who are low on the Trump profile (Bacon Jr. 2019, Enns and Schuldt 2019). Because politicians pay a penalty for trafficking overtly in racism, sexism, xenophobia, and conspiracy theorizing, most tend to engage in no more than dog-whistle politics (Haney-López 2015). This strategy presumably allows the benefit of activating voters' grievances without paying a cost of looking racist, for example. But Trump has also paid a penalty in that, given the strong economy, his approval ratings would presumably be higher had he not alienated so many Americans with his rhetoric (e.g., Brownstein 2019).

While Trump was good at activating underlying feelings of threat, he is not alone in cueing and redirecting orientations such as racism and sexism. We have already seen other mimic Trump's language and policy stances across the world. Politicians do not have to be like Trump, but they can, if they choose to, activate in people what Trump has managed to activate – it is there for the taking. This style of politics may very well lead to realignment as some have

predicted, but it may also motivate individuals to act on their grievances in ways that are both unsavory and undemocratic.

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