Class and cultural conflict in America today: Lessons from the 2016 Presidential election

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Abstract The 2016 surprise election of Donald Trump has refocused attention on politically polarizing class and cultural tensions, including working-class anger towards urban elites, resentment towards the 'undeserving' poor,' and/or White anxiety associated with race and immigration. In this paper we address to what extent these each of these narratives is consistent with observed patterns of county- and individual-level socio-economic, demographic, and political outcomes. Our results are more supportive of White male working-class and near-poor resentment against those below the poverty line (particularly if they are Black) than against those in the (local) upper elite. We also find strong evidence consistent with the presence of "halo" effects around immigration and race, with home-county votes for Trump falling with greater local immigrant share of population, but increasing with greater nearby (but not local) immigrant share. On the other hand, increases in Trump support are associated with both greater local *and* greater nearby Black population. Both of these results are supportive of theories of "Black exceptionalism" and speak to the importance of local salience in understanding voting patterns.

Key words: Trump, 2016 presidential election, working-class resentment, inequality, race, immigration

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1 Introduction

The economic and social political tensions that have increasingly polarized America politics in the last decade have been the focus of both pundits' commentaries and a growing body of academic scholarship. For example, Cramer (2016) and Chua (2018) write of growing rural working-class bitterness towards urban elites, a narrative further supported by Autor et al. (2013) who document the economic losses in those regions hardest hit by globalization. On the other hand, Lakoff (2002), Cramer (2016), Tesler (2017) and Parker (2016) write instead of conservative political resentment related to evolving concepts of 'deservingness' of the poor. Gilens (1999), Tesler (2016) and Parker (2016) point to evidence of increasing racialization of American politics, while Margalit (2012), Hajnal and Rivera (2014), Abrajano and Hajnal (2015), and Garand et al. (2017) emphasize the political consequences of increased immigration and the perceived ensuing social and cultural clashes.

The surprise upset by Donald Trump in the 2016 US Presidential election has redoubled both popular and academic attention on these alternative (but not mutually exclusive) political narratives; White working-class resentment is widely believed to have played a major role in the Trump victory, but there remains a healthy discussion about the main focus of this resentment. A common perspective was summed up by Jim Tankersley writing in the *Washington Post* just after the election on November 11, 2016:

> For the past 40 years, America's economy has raked blue-collar White men over the coals. It whittled their paychecks. It devalued the type of work they did best. It shuttered factories and mines and shops in their communities. New industries sprouted in cities where they didn't live, powered by workers with college degrees they didn't hold.
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> They were not the only ones who felt abandoned by a rapidly globalizing economy, but they developed a distinctly strong pessimism in its face. On Tuesday, their frustrations helped elect Donald Trump, the first major-party nominee of the modern era to speak directly and relentlessly to their economic and cultural fears. It was a 'Brexit' moment in America, a revolt of working-class Whites who felt stung by globalization and uneasy in a diversifying country where their political power had seemed to be diminishing. (Tankersley, 2016)

The hypothesis that working-class resentment may be aimed at systems that privilege the urban, globalized wealthy is certainly consistent with recent academic research; for example Chua (2018) writes of the rise of increased tribalism in American class relations, with coastal elites increasingly seen as a market-dominant minority. Autor et al. (2013, 2016) show that workers in those "left behind" areas hardest hit by import competition from China were negatively affected in terms of job security and income, and Monnat (2016) also finds in her analysis of 893 counties in the Industrial Midwest, Appalachia, and New England that Trump outperformed Romney the most in those counties with the highest mortality rates from drug, alcohol, and suicide, which in turn she shows are associated with the degree of economic distress and proportion of working-class residents. Newman et al. (2015) find that residing in a more unequal county heightens rejection of meritocracy among low-income voters (while increasing it among high-income voters).

The spirit of Tankersley's assessment is similarly echoed in the political narrative revealed in the recent book "The Politics of Resentment" by the University of Wisconsin's Katherine J. Cramer (Cramer, 2016). Cramer's rural Wisconsin subjects expressed deep bitterness towards urban elites, a distrust of government, and a sense that they had been cheated by both. Sentiments, writes Cramer, that are rooted in "ideas about who gets what, who has power, what people are like, and who is to blame." Cramer elaborates on this more nuanced dimension of working-class politics further in an interview with Jeff Guo, published just before the November 2016 election in the *Washington Post*. When asked by Mr. Guo whether Trump support is mostly a phenomenon of racial or economic resentment, Cramer responds:

> It's not just resentment towards people of color. It's resentment toward elites, city people. And maybe the best way to explain how these things are intertwined is through noticing how much conceptions of hard work and deservingness matter for the way these resentments matter to politics. We know that when people think about their support for policies, a lot of the time what they're doing is thinking about whether the recipients of these policies are deserving. Those calculations are often intertwined with notions of hard work, because in the American political culture, we tend to equate hard work with deservingness. And a lot of racial stereotypes carry this notion of laziness, so when people are making these judgements about who's work hard, oftentimes people of color don't fare well in those judgements. In my mind, through resentment and these notions of deservingness, that's where you can see how economic anxiety and racial anxiety are intertwined. (Guo, 2016)

Cramer's view that working-class political resentment is related to concepts of 'deservingness' has a long academic pedigree (see, for example, Gilens, 1999; Petersen et al., 2012), albeit one generally applied to resentment aimed at a different group. While Cramer's rural White subjects apparently looked askance primarily at the 'deservingness' of elites and city folk, Robert Wade, citing George Lakoff (Lakoff, 2002), writes of conservative ideology that equates redistribution with "adults lacking in self-discipline and self-reliance; it is a welfare scrounger's haven" (Wade, 2012). Paul Krugman, writing in the *New York Times* in 2012, similarly acknowledges the political implication that "voters imagine that pledges to slash government spending mean cutting programs for the idle poor, not things they themselves count on. And this is a confusion politicians deliberately encourage" (Krugman, 2012). Appelbaum and Gebeloff, writing in 2012 also in the *New York Times*, report that "many people say they are angry because the government is wasting money and giving money to people who do not deserve it." Furthermore, when it comes to benefit resentment, familiarity may indeed breed contempt. Rather than developing an empathy for the poor, Appelbaum and Gebeloff point out that "some of the fiercest advocates for spending cuts have drawn public benefits. Many ... have family members who rely on the government. They often cite that personal experience as the reason they want to cut government spending" (Appelbaum and Gebeloff, 2012).

The idea that disdain for the poor, rather than envy of the rich, could be blowing the current political winds gained further support with both the March 2017 and February 2018 releases of the Trump administration's proposed 2019 budget, which slashes spending on programs that overwhelmingly benefit poorer Americans, earning it the moniker "The Nasty Budget," by the *New York Times* editorial board (NYT, 2018).

As Eduardo Porter (Porter, 2017) writes, also in the *New York Times*:

> The frazzled, anxious working-class men and women who voted for him like Social Security, Medicare and defense. Other government spending, not so much. Notably, there is little political cost for Mr. Trump - in fact, potential benefit - in going after means-tested programs for the poor. These programs appeal to two constituencies that working-class voters show little affinity for: the poor and urban liberal elites...

Mr Porter goes on to describe research by University of California professor Joan C. Williams (Williams, 2017) from her book "White Working Class: Overcoming Class Cluelessness in America":

> [W]hite workers' resentment of the safety net should not be surprising: They get next to no benefit from it. ... [T]hese struggling workers resent not only the poor beneficiaries of the government largess but also the liberal policy makers who seem to believe that only the poor are deserving of help. ... By contrast, they see themselves as hard-working citizens who struggle to make ends meet, only to be left out of many of the government programs their taxes pay for.

Moreover, a number of studies suggest that White political concerns about 'deservingness' may have become increasingly intertwined with attitudes towards race and immigration. Gilens (1999) suggests that across wealthy nations, Americans' relatively negative view of social welfare spending is primarily driven by Whites' perception that Blacks are 'lazy.' Furthermore, Tesler (2016) argues that the election of Barak Obama in 2008 sharply accelerated the racialization of American politics; for example, he reports that the share of Whites who identify the Democrats as more supportive of 'aid to Blacks' increased from 42% to 64% percent between 2004 and 2012. In further analysis, Tesler (2017) reports that Trump voters appear motivated by "their strong suspicion that African Americans are getting too much." Parker (2016) also argues that over time there has been a shift in racial attitudes among White Americans, who are now less likely to consider Blacks as 'inferior' but more likely to perceive them as having a 'poor work ethic.' Indeed, in an experimental question about a housing assistance policy, Luttig et al. (2017) report that White Trump supporters primed by exposure to a Black man were "more opposed to the policy, angrier about the policy, and more likely to blame beneficiaries for their situation" than when primed by exposure to a White man.

Immigrants may not have been spared this shift in perceptions either. Abrajano and Hajnal (2015) find that Whites who live in areas where immigration is encroaching are less likely to support public spending, especially spending that is more likely to benefit the poorer segments of the population. Both Garand et al. (2017) and Hajnal and Rivera (2014) argue that immigration may play an even bigger role than race in driving voting patterns and attitudes towards welfare spending, and all of these conclusions are consistent with Margalit (2012), who argues that a primary source of many individuals' fear of globalization is not as much the economic consequences of trade openness as it is the perceived social and cultural consequences.

On the other hand, the literature on "Black exceptionalism" (e.g. Sears and Savalei, 2006) argues that the unique nature, and sheer duration, of the history of White prejudice against Black-Americans implies that, while new immigrant groups may initially face high levels of stigmatization, in the longer run these other ethnic groups will assimilate faster. To the extent that a large part of recent immigration has involved Hispanic and/or Latino populations, "Black exceptionalism" implies that anti-Latino sentiment will be less important than prejudice against Blacks in shaping White's political attitudes. Indeed, recent research by Hopkins (2018) suggests that anti-Latino prejudice was not strongly predictive of Trump support, and that "immigration attitudes lose much of their predictive power when modeled alongside anti-Black prejudice." (Hopkins, 2018, p.4).

Thus while nearly everybody seems to agree that White working-class resentment was a major driver of Trump support, there persists a healthy discussion about whether this is primarily anger towards the urban and coastal elites' globalization-fueled spiraling wealth, working class economic insecurity associated with import competition, resentment towards the undeserving poor's government transfer programs, and/or White anxiety associated with changing cultural patterns associated with race and/or immigration. Of course these are not mutually exclusive possibilities, but the political, economic, and even philosophical implications of the alternative perspectives are distinct, and a better sense of their relative contributions is critical for understanding the current political environment.

This paper does not resolve this multichotomous dilemma, nor does it attempt to fully explain 'why Trump won.' Instead, the paper contributes to the ongoing discussion about the salient focus (or foci) of working class resentment by addressing a much more feasible research question: to what extent are the observed patterns in county-and individual-level socio-economic, demographic, and political outcomes consistent with each of these political narratives? More specifically, we model both county-level and individual-level support for Trump in the 2016 presidential election as a function of county-level patterns of income distribution, poverty, race, and immigration, controlling for a variety of additional economic, social, and demographic characteristics. This empirical strategy has some strengths and some limitations. The national scope and broad variety of socio-economic, demographic and political data available at the county level allow us to explore some dimensions of the research questions other approaches miss. On the other hand, at the county level we cannot directly identify individual votes (the so-called 'ecological' data issue). The individual-level survey data thus augments the county-level analyses to ensure our interpretation is consistent. However, neither the county- nor the individual-level analyses allow us to directly speak to national-level trends that are independent of county-level heterogeneity.

Nevertheless, by carefully structuring the research questions within these methodological constraints, the analysis turns up some surprising, new results and contributes some unique insights to the discussion: in particular, we show that controlling for median county income and a host of economic, social, and demographic characteristics as well state fixed effects, the observed patterns are more consistent with White male working class and near-poor resentment against those below the poverty line (particularly if they are Black) than against those in the (local) upper elite. We also find strong evidence consistent with the presence of "halo" effects around immigration and race, with home-county votes for Trump falling with greater local immigrant share (which allows for familiarity), but increasing with both greater nearby (but not local) immigration, and greater nearby (and local) Black population. Both of these results are supportive of theories of "Black exceptionalism" and speak to the importance of local salience in understanding voting patterns.

This paper proceeds as follows: section 2 describes the data and empirical methodology used in the analysis, section 3 describes and discusses the results, and section 4 provides a summary and discussion. A more detailed description of the dataset and full regression results for all tables is provided in the Online Appendix.

2 Data and Method

Data on the county-level income distribution comes from the 2016 release of the US Census Bureau's American Community (ACS) 5-year Survey and includes the top income threshold for each quintile of the income distribution (so, four thresholds), as well as the lower income threshold for the top 5% of the distribution. We also obtain data from the 2016 ASC survey on county-level total population, median household income, poverty rates, county-level measures of age distributions and unemployment rates, employment, urban share, education, labor force participation, and race-specific population shares and poverty rates. We also use supplemental data on racial poverty rates from the 2010 census and on non-English speaking households from the 2009 ASC 5-year release.

Additional county-level data include 2016 and 2012 Presidential election results made publicly available on Github.com by Tony McGovern, and the absolute numbers of voter registrations and turnouts from the U.S. Election Assistance Commission's (EAC) 2016 Election Administration and Voting survey (see the Online Appendix for details). We also collect data on exposure to import competition as measured by the average growth in import exposure between the 1990-2000 and 2000-2007 (Autor et al., 2013); in practice the greatest increase in this period is from China and thus we name this variable "China shock."

Individual survey data comes from the version 2 release of the 2016 Cooperative Congressional Election Survey (CCES16) (Ansolabehere and Schaner, 2017). We collect information on the respondent's county, vote choice in the 2016 and 2012 Presidential elections, household income, gender, race, age, and education, including only respondents who answered the post-election survey and who reside in a sample county included in the county-level analysis.

Forty-eight counties (less than 1.5% of the original sample), primarily small counties with very small Black populations and unstable Black poverty rates, were identified as outliers and dropped from the sample; a more detailed description of the outlier counties is included in the Data Appendix. All together we have complete data for a sample of 1910 county-level observations and 33,869 individual voter observations. Full information on data sources and definitions can be found in the Online Appendix, and summary statistics for all variables used in the analysis are presented in Table 1.

The estimation strategy is very straightforward; for the county-level analyses we model the county-level republican vote percentage as a function of quintile income thresholds and a variety of economic and demographic controls:

$$Trump\%_i = \alpha + \sum_k \beta_k x_{ki} + \mu_i, \tag{1}$$

Regression tables report coefficient estimates and their associated state-level cluster-robust p-values in parentheses. Asterisks in the tables indicate statistical significance at the .001, .01 and .05 levels, as explained in the tables' footnotes. Some regression specifications restrict the estimation to a subset of data and/or additionally control for state fixed effects, and this is noted both in the text and in the table.

Although the estimation *strategy* for the county-level analyses is straightforward, the estimation *interpretation* is less so. The use of so-called 'ecological' (aggregated) data for modeling political choice is subject to well-known limitations and these must be kept in mind both when designing the regression specifications and when interpreting the results. For example, if a county is characterized by a relatively high level of poverty and a relatively high proportion of votes for Trump (*ceteris paribus*), we do not know if it is the poorer people themselves voting in higher numbers for Trump, whether it is wealthier people who are voting more for Trump (for example because they resent government aid), whether *everyone* is more likely to vote for Trump due to a demonstration or other aggregate effect of having greater local poverty, or whether one group that might otherwise support Clinton is simply less likely to vote (for example, due to voter suppression measures). As we cannot tell the difference between these hypotheses it is important to structure research questions that can be tested within these methodological constraints - for example, to test for the latter possibility we can control for voter registration and participation rates.

On the other hand, some results are more straightforward to interpret; when we observe increased home-support for Trump associated with greater Black population shares in nearby counties, it is in fact impossible that neighbor-county Blacks are voting in the local home county. More generally, throughout this analysis we consider what the county-level correlation between the income distribution and the voting pattern would be expected to look like if there was elite resentment? poor-resentment? immigrant-resentment? So, although we do not observe "smoking gun" individual voter behaviour and cannot *prove* that particular votes were cast by particular groups in the county-level regressions, we can often test whether the aggregate patterns *are consistent*, or not, with particular hypotheses. Then, with enough evidence and well-crafted, implied empirical hypotheses, some hypotheses can be effectively ruled-out and others can emerge as most likely. We then further test the robustness of our conclusions by looking for the analogous patterns we would expect in the individual voter survey data.

The analyses at the individual level model individual i's choice to vote for Trump as a binary dummy variable; either they voted for Trump (Trump$_i$=1), or they didn't (Trump$_i$=0). As the dependent variable is a binary dummy variable, following the recommendation of Angrist and Pischke (2009), these regressions are estimated using linear probability models:

$$Trump_i = \alpha + \sum_s \gamma_s x_{si} + \epsilon_i, \tag{2}$$

In this case we cluster standard errors at the county level. Again, regression tables report coefficient estimates and their associated county-level cluster-robust p-values in parentheses, and where a model is restricted to a subset of data and/or include state fixed effects this is noted in the table.

While the results of the individual survey regressions are easier to interpret, it is wise to keep in mind that another limit to our ability draw broad conclusions from either our county-level or our individual-level results is that, to the extent that a political phenomenon we are interested in contains dimensions that are driven at a broader scale than our county-level unit of analysis, then of course county- or individual-level variation may not be able to identify those aspects of the phenomena. For example, if working class political preferences are formed at the national- or regional-level, such as the national-level perception of the emergence of a coastal economic elite discussed in Chua (2018), or the rural working-class bitterness directed at policy-makers in Madison discussed in Cramer (2016), rather than from local county-level conditions, then even if we observe that variation in voting outcomes is correlated with the proportion of working class households across counties, we are not able to (even suggestively) discriminate between hypotheses about national- or regional-level sources of those preferences. Thus our conclusions are limited to differentiating between potential alternative sources of resentment and anxiety that vary at the local county level.

3 Results

We begin by exploring the relationship between county-level support for Trump and attributes of the county-level income distribution. In Table 2 column (1) we model the Trump vote as a function of the shape of the county-wide household income distribution by controlling for the bottom income threshold of the top 5% of earners, and the top thresholds for the fifth (lowest, or Q5), fourth (Q4), and third (Q3) income quintiles. We find that counties with higher top 5% incomes have lower vote shares for Trump, while those with higher lowest quintile (Q5) income thresholds have more Trump voters; in other words, counties with wealthier elites voted more for Clinton, while counties with wealthier poor voted more for Trump.

To see whether the Q5 result may be related to the degree of poverty, in column (2) we additionally control for the county poverty rate. While the county-level Q5 threshold and poverty rate are correlated (with a simple correlation of 0.65), they are also distinct concepts with unique information with regard to the shape of the income distribution. Without controlling for the poverty rate, variation in the Q5 threshold would largely reflect differing poverty rates. As long as the poverty rate is below 20%, by controlling for the poverty rate, those counties with higher Q5 thresholds (but the same poverty rates) then must have more households in the bottom 20% that are not technically classified as below the poverty line (and if the poverty rate is above 20%, a higher Q5 threshold, controlling for the Q4 threshold, implies more households above the poverty line in the lower end of the fourth quintile). Indeed, we find that higher poverty rates are associated with more support for Clinton, but while the magnitude of the coefficient on the Q5 threshold falls, it is still positive and statistically significant; thus differing poverty rates alone cannot wholly explain our initial results in column (1).

The results presented in columns (1) and (2) of Table 2 suggest an interesting non-linearity in the relationship between household income and Trump support. Overall, the wealthier the county the more Clinton support there is. There is no evidence that higher inequality at the top end (e.g. a high top 5% threshold controlling for the Q5 threshold and median household income) increases support for Trump; to the contrary, the higher the top threshold the lower the Trump vote. At the opposite side of the income distribution higher poverty also increases support for Clinton. However, we consistently find that as the lowest quintile (Q5) threshold increases, voter support for Trump increases. It is important to keep in mind that we do not know who is doing the voting; if poverty is higher we don't know if those in poverty are voting for Clinton, if there is some kind of demonstration effect, or if another omitted factor that is correlated with poverty and with Democratic support is driving the results. Likewise just because Trump support increases with the Q5 threshold, we cannot be sure it is those Q5 voters who are voting in greater numbers for Trump.

To investigate this further in column (3) we explore the relationship between the Q5 income threshold and the Trump vote in more detail. Specifically, we divide the Q5 threshold into four groups represented by dummy variables: in the first group (Low1) the Q5 threshold is less than or equal to \$14,000 and comprises about 6% of the observations. A second group (Low2) consists of those counties with Q5 income thresholds between \$14,000 to \$18,000, and accounts for about 19% of the sample. The third group (Low3) includes counties with Q5 thresholds between \$18,000 to \$22,000 (about 32% of the sample), and a fourth group (the reference group) have Q5 thresholds are more than \$22,000. We find that the effect of the Q5 threshold in regressions (1) and (2) is being driven primarily by increases in the threshold from the Low1 to the Low2 group, and to a lesser extent to the Low3 group. In column (4) we control for median household income instead of the Q4 and Q3 thresholds, parse out the poverty rate by race, and additionally include controls for the racial distribution of the county population; the pattern of the Q5 threshold being driven by higher support for Trump in the Low2 counties is now even more apparent, with the coefficient on Low1 negative (though not significant) and the coefficient on Low3 losing significance. Although the precise income threshold for household poverty varies with household composition etc., the approximate poverty threshold for an individual in the U.S. is around \$12,000, so a possible interpretation of this pattern is that those counties whose bottom quintile of the income distribution sits just slightly above the poverty line (e.g. Low2) have more support for Trump, compared to those counties where the bottom quintile lies squarely below the poverty line (Low1), or wealthier counties where the bottom quintile threshold lies well above the poverty line (Low3 and Low4).

Interpreting the coefficients on the Q5 Low2 dummy variable in column (4) requires keeping in mind that the county-level top income threshold, median household income, and the poverty rate are all controlled for as well. Thus across county-wide income distributions with the same median, the same top end, and similar poverty rates, a higher Q5 threshold implies a bigger average income gap between those below the poverty line and those just above it, but still in the bottom 20% of all households. The distributional bulge of households above, but close to falling into, more severe poverty implied by this effect could extend into the lower end of the fourth quintile as well, so overall a reasonable interpretation of this pattern is that, compared to counties with otherwise similar median and top household incomes and poverty rates, most of the bottom quintile of households fall below the poverty line in Low1 counties, a relatively greater proportion of lower income households are clustered just above the poverty line in Low2 counties, and substantial numbers of households in the lowest quintile enjoy incomes well above the poverty line in Low3 and Low4 counties. The results from Table 2 suggest that in these middle "Goldilocks" Low2 counties there was a relatively higher vote for Trump. This relationship is robust to controlling for racial composition, and is consistent with the general pattern reported by Monnat (2016). Later in section 3.1.1 below we explore more explicitly the range of household incomes that display this disproportionate support for Trump to confirm our intuition.

3.1 Resentment of the local elite, the local poor, and Trump support

The results presented in Table 2 establish a provocative relationship between support for Trump and a lower quintile (Q5) household income threshold that lies between $18-22,000 (Low2). But, as discussed, we cannot be certain *which* households are more likely to vote for Trump. To rule-out or rule-in alternative hypotheses that could better explain this observed pattern, we consider what *additional* patterns we would expect to see if a hypothesis were true. Specifically, if we consider the hypothesized narrative that the resentment felt by the working class is focussed on those in poverty (for example because of perceived "unfair" government transfers), an auxiliary testable hypothesis that we should observe is that the support for Trump associated with "Goldilocks" Low2 counties increases when the local poverty rate is higher. In other words, we should observe positive and statistically significant coefficients on the *interaction* (multiplication) of Low2 and the poverty rate.

Thus in Table 3 column (5) we additionally control for the interactions of Low2 with White, Black, Hispanic, and Asian poverty rates. Because the list of control variables is now getting quite long, to keep the table tractable we now display only the most salient results, but full regression results are provided in the Online Appendix. As we see, in column (5) Low2 by itself is no longer statistically significant, and nor are the interactions of Low2 with the White, Hispanic or Asian poverty rates. However the interaction of Low2 with the Black poverty rate is positive (pro-Trump) and statistically significant, a pattern consistent with lower working-class resentment, as long as the resentment is understood to have a race component. Thus although we do not directly observe individual votes, we have derived a specific prediction about an expected nonlinear pattern in the county-level data if the "resentment of the poor" hypotheses were true, and tested this auxiliary hypothesis. Taken together, then, our results are consistent with the hypothesis that near-poor working class households exposed to higher local poverty are more likely to vote for Trump, but only if the households in poverty are Black. This is our first primary baseline result, which we now investigate in more depth, including testing for the analogous pattern in individual voter data and exploring alternative explanations that could also be consistent with this relationship.

It is important to keep in mind that in Table 3 column (5) we are controlling for the Black share of the population as well as for the Black poverty rate (both of which are negative, though only the latter statistically significant- see the Online Appendix for full regression results). So, the larger the Black community in a county and the higher the Black poverty rate, the more likely voters are to support Clinton. However, in Low2 counties, higher Black poverty also has an effect of *decreasing* support for Clinton and increasing it for Trump. Although this is county-level data, it is reasonable to assume that it is not the poor Blacks that are voting in higher numbers for Trump in these ''Goldilocks" counties, so this result gives us additional confidence in our interpretation of the Low2 pattern.

The result in column (5) is striking, but to minimize the chance that we mis-interpret the coefficient on the interaction between Low2 and Black poverty due to omitted variables, in column (6) we explore the robustness of the relationship between Low2 counties and Black poverty to additional county-level controls that may be related to both income distribution and support for Trump. Specifically, we additionally include county-level population size, age distribution, urban share, unemployment rate, male labor force participation rates, exposure to import competition (the so-called "China shock"), and the non-agricultural shares of employment in manufacturing and mining. The significant additional control variables all carry the expected sign; more urban counties have higher support for Clinton and counties with higher manufacturing and mining shares vote in larger numbers for Trump. Notably, the coefficient on the interaction between Low2 counties and the Black poverty rate remains remarkably stable and becomes even more strongly statistically significant.

To even further test robustness, in column (7) we add state fixed effects to our full set of county-level controls. The state fixed effects control for all relevant additional characteristics (observable or unobservable) that differ between states, but are common across counties within a state, that determine state-level average support for Trump. In other words, by including state fixed effects we investigate whether, across counties *within* a state, those counties with "Goldilocks" Low2 Q5 thresholds and relatively higher Black poverty rates (compared to other counties within the state), display relatively greater support for Trump. Including state fixed effects reduces the magnitude of the interaction of Low2 with Black poverty by half (from 0.214 to 0.123), but the coefficient remains robustly statistically significant. More precisely, since Low2 is a simple dummy variable, the total expected marginal increase in the Trump percentage for a one standard-deviation increase in the Black poverty rate (0.17) implied by the results of column (7) is $(0.123 - .033) * 0.17 = 0.015$, or just about a 1.5% increase in the expected Trump vote (in those counties with Low2 Q5 thresholds). Alternatively, the effect on the Trump vote share in Low2 counties at the mean of Black poverty (0.29), we get $-0.16 + 0.123 * .0.29 = 0.0197$, or approximately a 2% increase in Trump share compared to non-Low2 counties.

Finally, in Table 3 column (8) we continue to control for state fixed effects and explore an additional alternative (but again, not mutually exclusive) hypothesis, that there may also be resentment of immigrants driving Trump support. For example, Hajnal and Rivera (2014) finds that negative attitudes towards immigrants is an even more powerful predictor of Republican support than are racial attitudes. Abrajano and Hajnal (2015) warn that an anti-immigration backlash "could lead to increasingly strict and conservative policy making, shift the balance of power between Democrats and Republicans, and advantage rightward-leaning candidates throughout the country." (p.2). The analysis so far has not been consistent with this idea, as the coefficient on the share of non-English speaking households in a county is consistently negative (pro-Clinton), albeit not quite statistically significant, a pattern that is more consistent with both Rothwell and Diego-Rosell (2016) and Sorensen (2016) who both find that attitudes towards immigrants are more favorable in areas where people have more personal experience interacting with them. However, in our own analysis we do not know if our result emerges because the presence of immigrants provides a positive demonstration effect to the local native population, or whether it is the immigrant vote itself that is shifting the numbers (or both). However, if some voters increase support for Trump when Black poverty is higher, it is not so much of a stretch to consider this group might similarly increase support for Trump when county-level immigrant concentration is higher as well. Indeed, in their analysis of the effects of immigration on White voting patterns Hajnal and Rivera (2014) suggest as much, hypothesizing that:

> Immigration is likely to be especially threatening for those Americans who are less well educated and thus more likely to experience far greater direct competition with low-skilled immigrants for jobs and public services. (p.787)

Thus in column (8) we interact our variable for the share of households speaking a language other than English with our Low2 dummy; if this interaction term were also positive and significant this would be consistent with the immigrant-resentment hypothesis. However in column (8) we find the opposite -the coefficient is *negative* and highly statistically significant, suggesting a higher share of non-English speaking household moderates, not exacerbates, the pro-Trump impact of Low2. Of course, as we discuss elsewhere, this does not entirely disprove the immigrant-resentment hypothesis either; Trump voters may perceive a national immigration problem that is not correlated with county-level immigrant concentration or, as we explore further below, they may react to (less familiar) high immigration in nearby counties.

3.1.1 Individual voter analyses

The results from Table 3 are consistent with working class resentment of the (Black) poor, but as we have discussed, the aggregate county-level data do not allow us to *directly* test this hypothesis, and a concern could remain that our interpretation of the results may be confounding a demonstration or other aggregate effect with direct voter behavior. To check whether this could be the case, we exploit the large 2016 Cooperative Congressional Election Survey (CCES16) (Ansolabehere and Schaner, 2017), which as described above provides us with an effective sample of over 33,000 individuals surveyed before and after the 2016 Presidential election. By merging the individual level survey data with our county-level data, we are able to test whether the hypothesized relationships are apparent in individual voter data as well. Specifically, we test whether individuals are more likely to vote for Trump if they reside in a county with higher income inequality driven by top incomes, whether lower income voters in a similar "Goldilocks" Low2 income zone are more likely to vote for Trump, and whether this latter effect is higher if the county they reside in has higher levels of poverty.

Although there is no direct correspondence between individual household income and the Q5 quintile threshold figures from the county-level census (and, as discussed above, the *actual* household incomes associated with higher Trump support in Low2 Q5 thresholds cannot be determined from the county-level data alone), we construct three income categories that, given the constraints of the binned income data in the CCES16 survey, as closely as possible correspond to the intuition of the county-level Low1, Low2, and Low3 categories. In particular, our CCES equivalent Low1 dummy variable identifies respondents with household incomes between zero and $20,000, which should be close to or below the household poverty line in most cases. The CCES equivalent of Low2 then corresponds to households with incomes between $20-30K, and the CCES Low3 equivalent covers those households with incomes from $30-40K.

Finally, as it is, the hypothesis of White working class resentment of (Black) poor is actually about White *male* working class resentment (see, for example, Tankersley, 2016; Schaffner et al., 2018), so to identify those voters who fall into this category we create a dummy variable for White males (WM) and for White males with household incomes in the Low1, Low2, and Low3 categories, which we call WML1, WML2, and WML3, respectively. In Table 4 we then investigate whether voters in general, and WML2 voters in particular, behave as predicted by the county-level analysis, controlling for both individual voter as well as county-level attributes and state fixed effects.

In Table 4 column (9) we begin by exploring the CCES16 individual results most analogous to our county-level results from regression (4) in Table 2, controlling for state fixed effects in all regressions. Specifically, controlling for the county-level top 5% income threshold, the county-level household median income, county-level rates of White, Black, and Hispanic poverty, and the county-level racial shares of population (we drop 'Asian' as this was not a clear single racial category in the CCES16 survey, so Asian now becomes part of the reference category), we now also control for *individual*-level household income, gender, race, education level, and age category. We then include our dummy variables for the Low1-Low3 equivalent income categories, White males (WM), and White males on incomes below $20K (WML1), $20-30K (WML2), and $30-40K (WML3). Consistent with the results from regression (4) in Table 2, we find a highly statistically significant increase in the liklihood of White male voters in the Low2 income category (WML2) voting for Trump, and a slightly smaller and slightly less statistically significant increase for White males on Low3 incomes (WML3). From the coefficient estimates on on the Low2- and Low3-equivalent dummies (which are negative) we thus further note that the positive effect on Trump support of Low2 counties from the county-level results in Table 2 must be driven by White male voters. In column (10) we observe that these results remain remarkably stable when we additionally controlling for our full set of county-level controls, including the share of non-English speaking households, the total population, urban share, unemployment, male LFPR, import competition (the so-called "China shock"), and the employment shares of manufacturing and mining. Full results are available in the Online Appendix.

In Table 4 columns (11) and (12) we interact our WML2 dummy with the county-level White, Black, and Hispanic poverty rates. Consistent with the county-level analysis, we find that WML2 support for Trump does increase when local county-level poverty rates are higher, but again only for higher levels of Black poverty. The coefficient estimate on the interaction between WML2 and Black poverty remains highly stable and significant when we include our full set of additional county-level controls (in column 12). Thus, consistent with the county-level data, the analysis of individual voter behavior also suggests that as the county-level Black poverty rate increases, White males on low incomes are more likely to vote for Trump. More specifically, the results in column (12) imply that, evaluated at the mean of Black poverty, a WML2 voter is approximately 5.6% more likely to vote for Trump ($.415(.29) - .064 = 0.056$) than a white male with household income greater than $40K. At the same time, for a one-standard deviation increase in Black poverty (0.17), a White male on Low2 income is $((0.415-0.073)*0.17 = 0.058)$ 5.8% more likely to vote for Trump. This result is broadly consistent with the estimates from the county-level analysis from column (7) given that the county-level estimates apply to all households across the county, while our CCES16 estimates are for White males only.

Overall, the results from the CCES16 individual survey data in Table 4 are remarkably consistent with the results from the county-level analysis in Table 3. We find mostly negative (pro-Clinton) associations with higher top income thresholds, and thus no support for the hypothesis that greater local inequality driven by wealthy elites is increasing support for Trump. At the same time, our interpretation of the county-level pattern as consistent with lower-income resentment against the (Black) poor is also confirmed in the individual voter data; the likelihood that a White male with a "Goldilocks" Low2 income will vote for Trump is strongly related to the extent of Black poverty (but not White or Hispanic poverty) in the county in which he resides. The finding that the individual survey results coincide and reinforce our county-level analysis builds additional confidence that the county-level data indeed contains useful information that, with care, can be interpreted in a robust way.

3.1.2 Robustness and Alternative Mechanisms

The results presented in tables 3 and 4 are consistent and provocative, but to explore how robust the observed patterns are, in Tables 5 and 6 we consider a range of alternative explanations and specifications. In particular, in the county-level data we test whether voter registration or turnout rates could explain the observed patterns, and in the CCES16 individual data we examine voting patterns for White males in different income categories (namely, Low1 and Low3), also presenting some limited, preliminary evidence on the role of education. We control for state fixed effects in all regressions and, finally, in both the county-level and individual-level data, we also investigate how robust the observed patterns are to additionally controling for voting behaviour in the 2012 Presidential election.

First, at the county-level, in Table 5 columns (13)-(15) we consider the alternative hypothesis that the correlation between ''Goldilocks" Low2 counties, the interaction of Low2 with Black poverty rates, and Trump support is being driven by lower voter participation and/or turnout (for example by Blacks who would otherwise presumably vote for Clinton), perhaps due to increased voter-suppression measures. It is important to keep in mind that this alternative hypothesis can still be consistent with White working-class resentment of Black poverty - it is just the *mechanism* through which this resentment turns into aggregate political outcomes that is of interest; either White voters could turn out in greater numbers for Trump (as we observed in the individual survey data), or they could increase their voter-suppression efforts (or both). In column (13) we control for our estimated proportion of the voting age population that is registered to vote, in column (14) we control for the proportion of registered voters that voted (turnout), and in column (15) we control for overall estimated voter participation (i.e. the proportion of voting age adults who voted), also including state fixed effects in all regressions. The coefficients on both voter registration and voter participation rates are negative but not statistically significant; importantly, the Low2 dummy interacted with Black poverty rates remains both positive and robustly statistically significant, with a stable coefficient estimate that is almost identical to that of Table 3 column (7), suggesting that voter registration and participation cannot explain the increased county-level vote for Trump associated with the combination of "Goldilocks" counties and higher Black poverty rates.

In Table 5 column (16) we replicate the specification from column (7) in Table 3 but additionally control for the percentage of the vote won by Republican candidate Mitt Romney in the 2012 Presidential election ('Romney 2012 %'). This approach to controlling for the 2012 Republican vote share is similar to modeling the excess share won by Trump in 2016 over Romney in 2012 (i.e. modeling Trump2016 - Romeney2012), but with the advantage that we don't impose the *ad hoc* constraint that the coefficient is 1 on the Romney 2012 share. The Romney variable essentially captures, in one variable, all the county-level characteristics that determined the Republican vote in the 2012 election, including any income-, race- and/or poverty- related relationships. Indeed, the model in column (16) controlling for both state fixed effects and the Romney 2012 vote share explains over 97% of the variation between counties in the Trump vote. The coefficient on the Top 5% threshold nevertheless remains negative and still robustly statistically significant. The coefficient on the interaction between Low2 and Black poverty falls considerably in magnitude, but it remains positive and, with a p-value of 0.08, is still statistically significant at the 10% level. Thus there is evidence that a "resentment of the poor" phenomena in Republican voting patterns was already salient in the 2012 election, but has increased further in strength through a Republican Presidential campaign remarkable for its degree of racial divisiveness.

Secondly, in Table 6, we explore the robustness of the main result from the CCES16 individual voter survey analysis from Table 4 column (12). In particular, we investigate the degree to which an increase in Trump support in response to higher Black poverty is unique to White males in the Low2 income category - after all, in Table 4 columns (9) and (10) we also observe a smaller bump in Trump support from White males in the Low3 income category as well. Thus in Table 6 columns (17) and (18) we interact White males from the lower Low1 and the higher Low3 categories (WML1 and WML3, respectively) with county-level rates of White, Black and Hispanic poverty. However none of these interaction effects are statistically significantly different from zero. Thus among the individual voter results we find that Trump support increases with Black poverty rates only among those White male voters in a "Goldilocks" Low2 household income bracket.

In Table 6 column (19) we investigate to what extent low education may explain the results on the interaction of WML2 and Black poverty rates. Specifically, we create a fourth dummy variable for White males with a high school degree or less (WMHS) and interact this with our racial poverty rates. Having a low education level of less than or equal to High School does indeed significantly increase support for Trump, however none of the interaction effects of WMHS with racial poverty rates are statistically significant. Thus it appears that the political salience of local Black poverty is more likely to be a function of income than of low education, but more finely detailed analysis of this question would be a fruitful avenue for future research[1]. Overall, the results from Table 6 show that the positive relationship between White males on Low2 incomes, Black poverty, and Trump support is not found among White male voters with either lower (Low1) , or slightly higher (Low3) household incomes, nor is it found among White male voters with a high school education or less.

Lastly, in Table 6 column (20) we again control for past voting record, in this case augmenting our main CCES16 result from Table 4 column (12) with an indicator of whether a survey respondent voted for Mitt Romney in the 2012 Presidential election. Again, the Romney variable should control for all characteristics (observable and unobservable) that drove a voter's candidate decision in 2012, and indeed it is a highly significant predictor of the likelihood of a respondent voting for Trump in 2016 (with a t-statistic of 143!). Again, consistent with the county-level results from Table 5 column (16), the coefficient on the Top 5% threshold remains negative and significant. Furthermore, the coefficient on the interaction of WML2 with county-level Black poverty rates falls by half, but nevertheless remains positive and still statistically significant, this time at the 5% level.

Taken together, the results in Tables 3 - 6 provide evidence across both county- and individual-level data that is more consistent with the hypothesis that resentment of the poor, and in particular resentment of Black poor, is a more important driver of Trump support than is resentment against local economic elites. We discuss the theoretical implications of these results more extensively below in Section 4, but for now turn the analysis to explore this surprisingly salient role of race and ethnicity.

3.2 "Halo" effects of Immigration and Race

So far we have found significant and robust patterns of Trump support consistent with near-poor working-class resentment of local (Black) poor populations, but not with resentment of local immigrant populations. However in Europe some social scientists have identified what they call the "halo effect," which Amanda Taub describes in the New York Times as "a phenomenon, repeated across Europe, in which people are most likely to vote for far-right politicians if they live close to diverse areas, but not actually within them." (Taub, 2017) For example Taub cites research from both Sweden (Rydgren and Ruth, 2013) and London (Kaufmann, 2015) that describe

[1]To illustrate how future research might make use of census and survey data we provide a preliminary analysis of the role of education in the Online Appendix.

communities that are "close enough to immigrants to feel they are under threat, but still too far to have the kinds of regular, friendly interactions that would dispel their fears." (Taub, 2017). Sorensen (2016) likewise finds that although non-Western immigration to Norway does indeed initially increase anti-immigration attitudes, the effect is modest and tends to burn out quickly as people gain experience interacting with the newcomers.

In the U.S. there are fewer studies on the salience of geography for understanding the relationship between immigration and native voters' political preferences. Abrajano and Hajnal (2015) conduct arguably the most comprehensive analysis, finding that Whites who live in states with higher shares of Latinos are more likely to support Republican candidates. However when they include local zipcode-level data in their analysis, the results are not statistically significant. Nevertheless, the zipcode unit is likely too small an area given the hypotheses under study, and they do not provide analysis of larger-area neighborhood effects. Edsall (2017) finds stronger evidence, however, concluding that: "Trump's anti-immigrant, racially loaded messages resonated most powerfully among voters living in the least diverse, most racially isolated white communities. It is in these locales, which are experiencing the earliest signs of minority growth, that anxiety over approaching diversity is strongest."

Thus to test for a kind of European-style "halo effect" in our U.S. county data, we consider whether local Trump support might depend not only the local economic and demographic conditions but also on those from nearby counties. To do this we draw a 50-mile radius circle around the center of each county and calculate the maximum value of several salient variables within any county that overlaps this 50-mile range. Thus "halo White poverty" is the highest value of White poverty found in any nearby county within a 50-mile radius. Then, in Tables 7 and 8 we exploit both county-level and individual-voter level data, respectively, to test whether the these "halo" variables (including racial shares of the population, poverty rates (by race), shares of households that are non-English speaking, or top income thresholds) also have an impact on the predicted Trump vote for the original home county.

In Table 7 column (21) we include "halo" Top 5% income thresholds and "halo" versions of all the race variables to our baseline set of county-level controls (again, full regression results are available in the Online Appendix). A higher local home-county Black or Hispanic share of the population significantly increases support for Clinton, potentially either because these voters are supporting the Democratic ticket directly, and/or because the local population has become more mutually tolerant. However, a higher "halo" share of Blacks or Hispanics in *neighboring* counties (controlling for local share) *increases* home-county support for Trump. This result is strongly consistent with European "halo" effects and, moreover, since the neighboring-county population cannot vote in the home county, there is less ambiguity in this case in terms of guessing about which group is likely increasing support for Trump.

In column (22) we additionally control for state fixed effects; in other words, we explore to what extent we observe “halo” voting behavior across counties *within* states, relative to state-level averages of White, Black, Hispanic and Asian population shares, and state-wide average Trump support. Note that in this case including state fixed effects is not necessarily a convincing test of robustness of “halo” political patterns; across the U.S. there is a high degree of state-level heterogeneity in average racial and ethnic population shares, and to the extent that the state-wide racial and ethnic shares and state-wide political voting behavior are related, controlling for state fixed effects effectively eliminates this factor and may, in effect, be ‘throwing the baby out with the bathwater’. For example, some western states like Arizona have large Hispanic populations and also traditionally display strong Republican support. However if one of the salient *reasons* for the stronger Trump support is the presence of a larger Hispanic population, then state fixed effects will obscure this; we will only observe “halo” effects if those Arizona counties with higher than average (for Arizona) Trump support also have neighbors with higher than average (for Arizona) Hispanic populations.

Nevertheless, keeping this methodological caveat in mind, the results from column (22) are striking. The introduction of state fixed effects reduces the magnitude and eliminates the statistical significance of the coefficient on “halo” Hispanic share (though as discussed above, we do not consider this to be *strong* evidence against “halo” effects of Hispanic populations) but, although greatly reduced, the coefficient on “halo” Black population remains positive and highly statistically significant. The result in column (22) is thus consistent with other recent research on “Black exceptionalism”, including Hopkins (2018), whose analysis of 12 waves of panel survey data between 2007 and 2016 finds that White’s voting preferences are consistently and more strongly driven more by prejudice towards Blacks than by prejudice towards Latinos.

The results on U.S. “halo” effects of race on voting behavior underscore the importance of race in U.S. elections and help put the earlier results from section 3.1 into perspective. However, the literature on European “halo” effects primarily deals with the voting patterns of natives in response to *foreign* immigration. Arguably, in the U.S. the population share of Hispanics may also serve as an indication of the share of immigrants (for example as in Abrajano and Hajnal, 2015), so that the results from columns (21) and (22) could be interpreted as providing (somewhat ambiguous) support for such a phenomenon. But in column (22)-(25) we define ‘immigrant’ more conservatively, as those households that do not speak English in the house. First, in column (23) we control for both local share of non-English speaking households and the “halo” share. Consistent with results on the local share of non-English speaking households in Tables 3 and 5, we find a negative but not statistically significant relationship with county-level Trump support.

However, we have several methodological reservations about the model specification of column (23); first, as discussed above, the inclusion of state fixed effects may make it very difficult to detect “halo” effects of immigrants, even if they exist. Second, while the theoretical discussion and empirical patterns of European "halo" effects suggests that tolerance increases locally as natives become more familiar with multicultural populations over time, our data comes from the 2016 ASC release and to the extent that measured current population shares may reflect *recent* immigration (at least in some places), there may not have been sufficient time for tolerance to emerge to a sufficient degree to show up in the 2016 political voting patterns.

Thus in Table 7 column (24) we address both of these concerns by dropping the state fixed effects and additionally controlling for the share of non-English speaking households in from the ASC 2009 release. The results from column (24) are now strongly consistent with neo-European "halo" effects for immigrants; while in previous regressions the coefficients on *current* 2016 share of non-English speaking households tended to be negative but not statistically significant, in column (24) when we control for local immigrant share from 2009, the effect on Trump vote of more prolonged exposure to higher immigrant share is negative and now also highly statistically significant, while the *current* 2016 share of immigrants is no longer significant at all. This result is consistent with voters needing time to become familiar with immigrant populations and to adjust their voting preferences, and/or it may be that the 2009 pattern represents a cross-county distribution that, prior to the Great Recession, was relatively more stable and thus had a more enduring impact on (slower-adjusting) perceptions and preferences. This result that older, more established patterns of immigrant population shares appear to be more salient for current local voting behavior than current patterns is also consistent with prior research by (Rydgren and Ruth, 2013) and (Kaufmann, 2015), who both find that increased familiarity with immigrants leads to tolerance.

While (sustained) local exposure to immigrants is associated with more support for Clinton, at the same time, we observe from the results in column (24) that the higher the "halo" share of immigrants in a neighboring county, the *greater* the local home-county support for Trump. This "halo" result provides new empirical evidence on the geographical salience of U.S. immigration politics, and is arguably inconsistent with experimental results from Hainmueller and Hopkins (2015), which suggest that Americans' preferences over who constitutes a 'desirable' immigrant varies very little with party affiliation. Furthermore, additional analysis of the "halo" effects on lower income (Low2) voters (not reported but available upon request) suggests that the pro-Trump, anti-immigrant "halo" effect of a higher immigrant population nearby is potentially wide-spread among both the working class and broader population.

In column (25) we reintroduce state fixed effects (with the associated caveats as discussed above) and find that the results from column (24) remain reasonably robust; we still find a very significant negative effect on Trump support of older (2009) local immigrant populations, no impact of *current* immigrant population levels, and evidence of pro-Trump "halo" effects of (current) immigrant share, albeit now not quite significant at the 5% level (with a p-value of .066). Specifically, the results from column (25) suggest that a one standard deviation increase in immigrant (non-English speaking) population (0.0486) in neighboring counties leads to a $0.277 * 0.0486 = 0.0135$ 1.35% increase for Trump support in the home county. At the same time, however, a one standard deviation increase in immigration in the home county is associated with a 2.6% *decrease* in Trump support.

The county-level analysis presented in Table 7 provides strong evidence of neo-European "halo" effects of race and immigration, and suggests compelling, albeit indirect, evidence of (lagged) local assimilation effects. In particular, at the county level, if we observe higher local immigrant (or Black, or Hispanic etc.) share of population and lower support for Trump, there is always some ambiguity about what specific local group of voters is driving an observed trend, so we cannot definitively say whether this outcome is due to increased general acceptance of immigrants, or the immigrants themselves voting in a particular way. Thus to verify our interpretation of the county-level results and more directly investigate the phenomenon at the individual voter level, in Table 8 we merge our county-level "halo" variables with the individual-level CCES16 survey data. In this way we can also restrict the sample to only White respondents, which ensures that we are observing (White) voters' response to trends in local Black populations, and - assuming White voters are unlikely to live in non-English speaking households - minimizes the chance that we misinterpret coefficients on immigrant shares.

The results of the CCES16 "halo" analysis are presented in Table 8 (again with full results available in the Online Appendix). In columns (26)-(28) we restrict the sample to White voters only, and for the methodological concerns discussed above, in column (26) we start with a model that omits state fixed effects. Among White voters we find a higher local Black share of population strongly increases support for Trump, as does a higher Hispanic share, thought this latter effect is considerably smaller in magnitude and less statistically significant. Similarly, we find strong "halo" effects of higher Black and Hispanic shares in neighboring counties, although again the magnitude and statistical significance of the coefficient for Hispanic share is considerably lower. In column (27) we include state fixed effects, and while both the local and "halo" effects of a higher Black share are still positive and statistically significant, consistent with the county-level analysis in Table 7, the statistical significance of both coefficients on the Hispanic shares is eliminated. Again, as in the county-level analysis, for the reasons discussed above we do not necessarily consider this to be strong evidence against "halo" effects for Hispanic populations, but a reasonable interpretation is that, to the extent they exist, the White voting reaction to local and nearby Black populations is considerably stronger than to Hispanic populations. Thus the individual-level "halo" results are again consistent with Hopkins (2018) and broadly supportive of "Black exceptionalism."

The analysis from Table 7 suggested that racial and/or culturally-based voting preferences may take some time to evolve, so in Table 8 column (28) we additionally control for the local White, Black, Hispanic and Asian population shares from 2010. We find that while having a historically higher Black share of population (controlling for current share) has a *negative* (and significant) effect on White support for Trump, controlling for past share, a higher *current* Black share has a very large *positive* and statistically significant effect. We also still observe a "halo" positive effect on White Trump support of higher neighboring Black population shares. While the coefficients on past, current, and "halo" Hispanic share follow the same pattern, they are not statistically significant (though keep in mind we are also controlling for state fixed effects). Taken together, the results suggest that there may be some local familiarization and "halo" effects similar to that found in the European "halo" literature associated with local Black and (perhaps) Hispanic populations and White voting patterns; future research that examines these time-lag and spatial-lag elements of racial perceptions and political preferences may shed more light on these processes.

In Table 8 columns (29)-(31) we use the full sample of survey respondents to explore the relationship between Trump support and non-English speaking (immigrant) population shares. In column (29) we again omit state fixed effects; we find a negative but not statistically significant effect on Trump support of *local* immigrant populations, but a strong and significant pro-Trump effect of "halo" neighboring immigrant populations. In column (30) we reintroduce state fixed effects and the "halo" pattern of a pro-Trump response to nearby immigrant populations persists, although, with a p-value of 0.054, just barely misses significance at 5%.

As discussed above, the county-level analysis suggested that local political reactions to immigrant population may take some time to evolve, so in column (31) we additionally control for older local immigrant share in from the 2009 ASC release. Consistent with the results at the county level, we find that the share of non-English speaking households in 2009 is associated with a significant negative effect on Trump support, while the effect of *current* immigrant share in 2016 is positive. Moreover, this pro-Trump effect of higher current immigrant share (controlling for past share) is now statistically significant. We also find positive pro-Trump effect of higher "halo" immigrant shares in neighboring counties that is now statistically significant at conventional levels. Taken together, the results in column (31) suggest that for a one standard deviation increase in the immigrant population in neighboring counties, home support for Trump will increase $0.302 * 0.0486 = 0.147$ about 1.5%. Conversely, a one standard deviation in the home population of immigrants is associated with a 2.3% *fall* in Trump support, results that are strikingly similar to those obtained from the county-level analysis in column (25).

Taken together, the evidence from Tables 7 and 8 provides strong support for U.S. neo-European political "halo" effects both with respect to race as well as immigration. Controlling for local conditions, sustained exposure to more immigrants locally is associated with lower support for Trump, while higher immigrant shares nearby (but not so close as to bring reassuring familiarity), or sudden local increases, may seem more of a threat, generating increased support for local anti-immigrant political positions, including support for Trump. As in the European cases discussed in Rydgren and Ruth (2013) Sorensen (2016) and Kaufmann (2015), local exposure to immigrants (but not to Blacks) is more than enough to completely offset this "halo" effect, however: the coefficient on local share of immigrants is not only pro-Clinton but also almost twice the magnitude of the pro-Trump effect of higher neighbor share.

The evidence here on "halo" effects for Hispanics is more ambiguous. The definition of "White" and "Hispanic" is not mutually exclusive, and *if* the pattern of Hispanic population concentration breaks mostly across state lines (an open question), then the elimination of between-state variation by the use of state fixed effects would greatly diminish the power of our approach to detect "halo" effects. The ambiguity of our analysis mirrors ambiguity in the current literature; as Hopkins (2018) notes, while some researchers find evidence of increasing importance of Hispanics in shaping White voting patters (for example, Abrajano and Hajnal, 2015), others point to evidence of enduring "Black exceptionalism." Taken together the analysis here does provide more support for the idea of "Black exceptionalism," and future research combining different methodological approaches may prove helpful in clarifying this debate.

4 Discussion

While a significant plurality of political pundits seem to agree that White working-class resentment played a large role in the surprise 2016 Trump victory, there remains a healthy discussion about what group they resent the most. Academic scholarship has suggested several alternative (but not mutually exclusive) hypotheses: Cramer (2016) and Chua (2018), among others, suggest White working-class resentment of the globalized urban elite; Autor et al. (2013, 2016) also point to globalization and to the economic insecurity introduced by increased import competition; Krugman (2012), Williams (2017) and Tesler (2017) point to White working-class resentment of government transfers to the poor; and recent work by Abrajano and Hajnal (2015), Hajnal and Rivera (2014), Tesler (2016), Parker (2016), Luttig et al. (2017) and Rothwell and Diego-Rosell (2016), among others, all argue that political preferences are increasingly driven by cultural views and social identity, with the consequence that race and immigration are playing an increasing role in U.S. election results.

In this paper we exploit the broad variety of aggregate economic, social, and political information available at the county- and individual-level to explore the extent to which the observed patterns are consistent with these various not-mutually-exclusive hypotheses. The analysis overall does not allow us to fully resolve the multichotomous dilemma at hand, nor do we attempt to definitively explain 'why Trump won;' nevertheless, even taking into account the caveats associated with the data and method, overall our results are more consistent with some of these hypotheses than others, and are strikingly similar across the county- and individual-level datasets.

First, controlling for median household income, we find no evidence that higher top income share (in other words, increased local top-end inequality) leads to more support for Trump. Quite to the contrary, the higher the top 5% income threshold, the greater the Democratic vote, and this results remains robust even in individual-level data where we control for voters' own household income. Indeed, increases in local top-end inequality remained significantly pro-Clinton even when controlling for patterns from the 2012 Presidential election, suggesting that this trend is even stronger for Trump than it was for Romney. This robust result runs contrary to what one would expect if the 'resentment of the rich' story were the primary driver of the 2016 election, and is similarly inconsistent with some recent analysis (albeit at a national level) suggesting that inequality might endogenously drive politics to the right (e.g. Barth et al., 2015). Of course, our analysis is of variation at the county-level, so to the extent that any national-level resentment of higher income elites drove Trump support across all counties independently of local conditions (such as the kind of broad-based perception of Romney's elitism discussed in Bartels, 2013, or the capital-focussed resentment reported in Cramer 2016), our approach would not be able to identify it.

On the other hand, Hersh and Nall (2016) cite Tobler's Law that "everything is related to everything else, but near things are more related than distant things," to emphasize the importance of local context in explaining voter behavior, and the idea is a key concept in discussions of the importance of *issue salience* in driving political preferences. In particular, scholars have theorized that voters' issue preferences are more likely to drive political choices when both the issue position of a party is clear, and when the issue is not only important to the voter but also *personally salient* (see, for example, Carsey and Layman, 2006; Ansolabehere and Puy, 2018). While increasing political polarization around issues of race has been a growing trend for at least a decade (Tesler, 2016; Hopkins, 2018), in the case of the 2016 election the Trump campaign famously broke all norms of mainstream political speech to target racial and ethnic stereotypes in its rhetoric (see, for example, Schaffner et al., 2018; Hopkins, 2018). Thus, while appeals to economic, racial, and cultural anxiety all do play out at the national level, theory and evidence would suggest that the political effects may be especially potent among voters for whom local conditions render those messages particularly personally salient. So, when we observe that *local* differences in income spread between the lowest and highest earners does not by itself seem to generate support for Trump, a possible interpretation is that local-level top-end inequality is either not very personally salient for most voters, or that to the extent that it is, voters decided that Clinton's platform was more likely to deliver an effective remedy. In the event, to the extent that national- and local- level reaction to top-end inequality might be inconsistent, perhaps the larger conclusion of these results is that further research is needed.

Second, we find a novel nonlinearity in the relationship between low household incomes and support for Trump. Specifically, we find that while increases in poverty, and increases in overall average income generally, are both associated with more support for Clinton, for those voters whose household income falls into a "Goldilocks" range above, but precariously near, the poverty level, there is a statistically significantly greater degree of support for Trump. From the individual survey data we find the county-level result is driven by White male voters, and that the probability that a White male on a "Goldilocks" (Low2) household income (between $20-30K) is about 6% more likely to vote for Trump than White men in households with lower or considerably higher household incomes.

By itself this "Goldilocks" pattern does not shed light on the source of White male Low2-income voters' motivations, but the extant theories do give rise to some auxilliary testable hypotheses. Specifically, as we have discussed, scholars such as Williams (2017) have pointed to resentment of government programs to aid the poor as a driving factor behind rising populism among working class Whites. Furthermore, while there is undoubtedly a national-level dimension to this narrative, issues related to poverty and social welfare are likely more *personally salient* for those voters who live close to, and/or have experience with, effected populations. In turn, in line with research by scholars such as Carsey and Layman (2006), these voters whose local circumstances make those topics more personally salient may have responded with greater enthusiasm to the Trump campaign messages. Taken together, then, theories of poor-resentment and the political importance of personal salience suggest that variation in local poverty may matter, and in particular that Trump support of the near-poor "Goldilocks" voters should be higher when local observable poverty (and associated government assistance) is greater.

We test this auxiliary hypothesis in both the county- and individual-level data and find strong and consistent evidence that, indeed, support for Trump increases among "Goldilocks" Low2 income (White male) voters when local poverty is higher, but only when the local poor are Black. We find no analogous increase in Trump support associated with higher rates of White or Hispanic poverty. Specifically, we estimate a one standard-deviation increase in the county-level Black poverty rate translates into a 1.5% increase in support for Trump in "Goldilocks" counties at the county-level, and a 5.8% increase in the likelihood that a White male on a Low2-equivalent household income (between $20-30K) will vote for Trump at the indvidual level. These two sets of result are broadly consistent, given that the county-level effects apply to all households, while our CCES16 individual estimates are for White males only.

This is our third main result, and in further explorations of the robustness of this empirical pattern, we find that the relationship remains statistically significant with the inclusion of state fixed effects, which controls for all unobservable characteristics that are common across counties but differ across states, such as “red” state - “blue” state differences. It is also robust to controlling for voter registration and voter participation, suggesting that while voter suppression may be an issue, it does not by itself explain the observed pattern. Neither do we observe any change in Trump support among White males on lower (Low1) or higher (Low3) household incomes in response to higher poverty rates (of any race), confirming that the observed political response to higher Black poverty is unique to White male voters from households with “Goldilocks” Low2-level incomes. Finally, the result is robust (moderately so in the county data and solidly so in the individual data) even when we control for the results of the 2012 Presidential election, suggesting that either the income, poverty, and race distributions have shifted, or the underlying sentiments driving the political outcomes have become more pronounced (or both) between 2012 and 2016.

This finding - that White, male “Goldilocks” voters are more likely to vote for Trump when local Black poverty is higher - is consistent with a combination of recent research using different methodological approaches. Using quantitative census and survey data, a number of researchers (see for example Monnat, 2016, and Rothwell and Diego-Rosell 2016) also find increased Trump support among lower-income working class households. Williams (2017), using qualitative analysis that builds on ideas explored in earlier work such as that by Gilens (1999) and Lakoff (2002), argues that resentment of government programs to help the “undeserving” poor is an increasingly salient driver of working class voter choice, and Tesler (2017) cites evidence suggesting this sentiment is even stronger when referring to Blacks. Tesler (2016) and Parker (2016) draw upon diverse sources to document the increasing racialization, and in particular the White reaction to Black population patterns, of U.S. voter behavior. Hopkins (2018) further argues, based on longitudinal survey data, that the political effects of Blacks on White voters is consistently and significantly greater than the effect of Hispanic populations. Luttig et al. (2017) brings together these results on “Black exceptionalism” with the “resentment of the poor” arguments, presenting experimental evidence that White attitudes towards Government benefits are moderated by the race of the recipient, and in particular that the response to cues of Black poverty is considerably more negative.

These results may also help shed light on an empirical puzzle revealed in Rothwell and Diego-Rosell (2016), who in pre-election survey data find that Trump supporters are economically better off than average, but tend to live in areas that are comparatively less economically developed, surrounded by neighbors facing greater economic hardship with lower chances for upwards mobility. Rothwell and Diego-Rosell (2016) speculate that perhaps Trump supporters are more concerned about the future chances for their children, and Ehrenfreund and

Guo (2016), discussing the Rothwell and Diego-Rosell (2016) analysis in the *Washington Post*, suggest that Trump supporters may be richer than their neighbors but still be worse off than they were in the past; in the event, the paradox remained something of a mystery. However this pattern may be reconciled if, consistent with our own findings, Trump support is instead driven by voters who themselves are not precisely poor or unemployed, but whose resentment of government transfers is aggravated by relatively close proximity to - and thus the personal saliency of - the perceived beneficiaries of those programs.

Finally, our results are also consistent with scholarship that argues that stronger political preferences are more likely to emerge in voting behavior when both the party position is clear and the issue in question is personally salient to the voter (see, for example, Carsey and Layman, 2006; Ansolabehere and Puy, 2018). During the 2016 Presidential election it was hard to miss the Trump campaign's uniquely provocative position on race, and White "Goldilocks" voters are arguably the non-Black (and non-ultra poor) group most likely to be personally exposed to local Black poverty, certainly more likely than higher income voters.

This last point is also important for clarifying one of the primary limitations of this analysis. The finding that only White male "Goldilocks" voters display increased Trump support when local Black poverty is higher does *not* constitute strong evidence that it is *only* this demographic and income cohort for which cues of Black poverty are politically salient. Our data includes only variation in political behavior that is associated with differences in actual, county-level Black poverty. If other groups' political behavior reacts more to national-level cues, then we will not be able to identify that relationship with our data. Thus it is more accurate to say that it is White male "Goldilocks" voters who seem, more than other kinds of voters, to respond politically to variation in *local* conditions of Black poverty. This could be either because this is the only group to be politically responsive to Black poverty, or because this is the only group for which local Black poverty is personally salient (or both). Our analysis cannot differentiate between these two explanations.

Our fourth result then emerges directly from our further exploration of the spatial properties of local salience for racial voting patterns. Throughout the analysis, and consistent with the results found by Rothwell and Diego-Rosell (2016), we find counties with larger shares of non-English speaking households are more likely to vote for Clinton. We also find no evidence that the pro-Trump effect of the near-poor is accentuated when the proportion of immigrants in a county is higher; to the contrary, we find a higher share significantly *lowers* Trump support in "Goldilocks" Low2 counties. However this interpretation becomes more complex when we look for "halo" effects like those observed in Europe by Rydgren and Ruth (2013) and Kaufmann (2015), who find that anti-immigrant sentiment is strongest in those regions just outside those with the highest immigrant shares: close enough to create the perception of a possible threat, but not close enough to generate comforting familiarity.

In particular, we find strong, novel evidence of a similar phenomenon in the US county voting patterns that is consistent across both the county- and individual- data; controlling for local conditions (where local immigrant populations are associated with increased Clinton support), higher immigrant share in *nearby* counties is associated with *greater* local home-county support for Trump. More specifically, at the county-level we find a one standard deviation increase in immigrant (non-English speaking) population in neighboring counties leads to a 1.35% increase for Trump support in the home county, while the same increase in immigration in the home county is associated with a 2.6% *decrease* in Trump support. In the individual-level analysis our estimates are strikingly similar; we find similar increase in the immigrant population in neighboring counties is associated with a 1.5% increase in support for Trump, while the same increase in the home population of immigrants is associated with a 2.3% *fall* in Trump support.

Moreover, consistent with the theory that familiarization leads to greater political tolerance, we find evidence that the local assimilation process discussed in Rydgren and Ruth (2013) and Kaufmann (2015) takes some time to evolve. Specifically, while the effect of *current* local levels of immigrant share is somewhat ambiguous (anti-Trump, but not significant), the effect of a higher immigrant population share that has resided in a county for at least 7-10 years (i.e. the share from the 2009 data release) is unambiguously negative (anti-Trump) and highly statistically significant. Furthermore, controlling for past (2009) immigrant share, higher *current* immigrant shares (who are less familiar) have the opposite effect, increasing local support for Trump in a similar, though of a smaller magnitude, impact as those of "halo" nearby immigrants.

Our fifth and final finding also emerges from the analysis of spatial "halo" effects; specifically, the analysis reveals some striking differences between local White voting patterns and both local and "halo" Black and Hispanic populations. In the county-level data, while increased *local* Black share of the population decreased support for Trump in the county-level data (most likely due to higher Democratic support among Blacks), higher shares of Blacks in *neighboring* counties increased it. Since neighboring Blacks cannot vote in local elections, the result highlights the impact of nearby Black populations on (presumably) White voting preferences. We confirm this intuition in the individual data; limiting the sample to Whites only, we now find not only that higher "halo" neighboring Black shares, but also higher *local* Black shares of the population, increase the likelihood that a White voter will support Trump. Our results are strongly consistent with numerous other studies (see, for example, Schaffner et al., 2018; Hopkins, 2018), that finds racial prejudice against Blacks to be an enduring, and likely growing, factor in White voting patterns.

Recent research has also highlighted the impact that shifting patterns of Latino immigration has had on White voting patterns (see for example, Abrajano and Hajnal, 2015; Hajnal and Rivera, 2014). However, while the effects of Blacks on White voting patterns is clear in our data, we find the political impact of local and "halo" Hispanic population shares to be considerably more ambigous. While initially we find positive, though smaller, pro-Trump "halo" effects of nearby Hispanic populations (in both the county- and individual- data), and evidence that a higher *local* Hispanic share also increases the likelihood a White voter will support Trump, none of these estimates are robust to the inclusion of state fixed effects in the analysis. As we discuss in section 3.2, this does not *necessarily* constitute strong evidence against the impact of Hispanic population on White voting patterns; an alternative explanation consistent with these results is that the political effects of Hispanic populations on White voters are also important (though not as significant as that found for Blacks), but play out more at the state level than at the county level. Either way, the findings do suggest that the political effects on White voters of local and "halo" Black populations is larger and more significant than that of Hispanic populations, and this is also consistent with our earlier results on the interaction of White male "Goldilocks" voters and poverty; we found significant interaction effects only for Black, but not Hispanic, poverty. Thus all together our results are broadly consistent with the literature on "Black exceptionalism" (e.g. Sears and Savalei, 2006).

Finally, throughout the analysis we also control for a broad set of county-level economic conditions and employment structure, as well as the county-level growth of import competition (the so-called "China shock"), with full regression results available in the Online Appendix. Consistent with previous research we find variation in economic conditions clearly do play a major role. However, the analysis presented here is designed to focus on the the role of income distribution and racial/cultural factors, with the additional economic variables included only as controls, and a more in-depth exploration of the relative contribution of these different factors is thus beyond the scope of this paper. For example, we find that, overall, the effect of import competition is modest and, as would be expected, rendered insignificant with additional economic controls capturing aspects of related local economic conditions, such as labor force participation and unemployment, (see the Online Appendix). The lack of strong results is not evidence against the "China shock" hypothesis, however - the Autor et al. (2013) story focusses more on a smaller subset of particularly acutely affected regions. More important for our analysis is the fact that the coefficients of interest remain stable and robust to controlling for variation in import competition, suggesting that our patterns of interest are statistically fairly independent of economic structure, including any "China shock" effect. Future research would be useful to further clarify how and to what extent these mechanisms interact.

In sum, overall we find little evidence to support the idea that the rise of Trump was buoyed by resentment of the rich. To the contrary, our county- and individual-level patterns are more consistent with White male working-class resentment of the poor, at least when those poor are Black. We also find strong evidence suggesting the presence of neo-European "halo" effects of immigrants, with county- and individual-level patterns that are similarly supportive of theories of "Black exceptionalism." Specifically, while prolonged local exposure to non-English speaking populations tends to moderate populist pro-Trump reactions, we find little robust evidence of any analogous tolerance emerging for local Blacks. And in all cases we find stronger White political reaction to Blacks than to Hispanics. Our contribution is necessarily partial and limited to variation explained by local county heterogeneity, but the results complement, and are consistent with, a growing body of scholarship on the role of race and culture in American politics and suggest productive directions for future research.

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5 Tables

Table 1: Summary Statistics

Variable	Obs	Mean	St. Dev.	Min	Max
County-Level Data					
Trump %	1910	0.60	0.15	0.04	0.91
Top5% lower threshold ($\times$10,000)	1910	16.38	3.41	8.60	25.00
Third quintile upper threshold (Q3)	1910	6.27	1.54	3.01	14.84
Fourth quintile upper threshold (Q4)	1910	4.04	1.07	1.73	10.45
Lowest quintile upper threshold (Q5)	1910	2.21	0.63	0.88	6.09
Q5=$\leq$\$14K (Low1)	1910	0.06	0.23	0.00	1.00
Q5=\$14-18K (Low2)	1910	0.19	0.40	0.00	1.00
Q5=\$18-22K (Low3)	1910	0.32	0.47	0.00	1.00
Q5$\geq$22K (Low4)	1910	0.43	0.50	0.00	1.00
Median HH income ($\times$ 10,000)	1910	5.08	1.29	2.09	12.57
White poverty rate	1910	0.12	0.04	0.01	0.35
Black poverty rate	1910	0.29	0.17	0.00	1.00
Hispanic poverty rate	1910	0.26	0.12	0.00	1.00
Asian poverty rate	1910	0.16	0.18	0.00	1.00
White share of population	1910	0.82	0.15	0.09	0.99
Black share of population	1910	0.09	0.12	0.00	0.77
Hispanic share of population	1910	0.11	0.14	0.01	0.98
Asian share of population	1910	0.02	0.03	0.00	0.43
Non-English speaking HHs share	1910	0.024	0.032	0.00	0.41
Total population ($\times$100,000)	1910	1.48	3.20	0.01	52.28
China shock	1910	0.04	0.08	-0.63	0.80
Urban share	1910	0.55	0.28	0.00	1.00
Unemployment rate	1910	0.07	0.03	0.01	0.21
Male LFPR	1910	0.79	0.10	0.17	0.94
Manufacturing share	1910	0.13	0.07	0.01	0.50
Mining share	1910	0.02	0.03	0.00	0.43
Age $\leq$30 share	1910	0.39	0.05	0.14	0.71
Age $\geq$55 share	1910	0.30	0.06	0.07	0.69
Educ$<$High School	1910	0.14	0.06	0.02	0.52
Educ$=$High School grad	1910	0.33	0.07	0.07	0.51
Educ$\geq$University	1910	0.23	0.10	0.06	0.80
Voter registration rate	1747	0.81	0.13	0.11	1.87
Voter turnout rate	1747	0.75	0.12	0.11	3.28
Voter participation rate	1910	0.58	0.09	0.16	1.00
Romney share of 2012 vote	1632	0.59	0.14	0.08	0.94
2016 CCES Individual Voter-Level Data					
Voted for Trump	33869	0.40	0.49	0.00	1.00
HH income$\leq$\$20K (Low1 equivalent)	33869	0.09	0.29	0.00	1.00
HH income=\$20-30K (Low2 equivalent)	33869	0.09	0.29	0.00	1.00
HH income=\$30-40K (Low3 equivalent)	33869	0.11	0.31	0.00	1.00
HH income ($\times$100,000)	33869	0.742	0.592	0.050	5.00
Male	33869	0.45	0.50	0.00	1.00
White	33869	0.78	0.41	0.00	1.00
Black	33869	0.10	0.30	0.00	1.00
Hispanic	33869	0.06	0.23	0.00	1.00
Educ$\leq$High School	33869	0.23	0.42	0.00	1.00
Educ$\geq$University	33869	0.42	0.49	0.00	1.00
Age$\leq$30	33869	0.11	0.31	0.00	1.00
Age$\geq$55	33869	0.45	0.50	0.00	1.00

Table 2: County-Level Income Distribution and the Percentage Vote for Trump

	(1) Trump %	(2) Trump %	(3) Trump %	(4) Trump %
Top 5 %	-0.020***	-0.019***	-0.019***	-0.016***
(lower threshold)	(0.000)	(0.000)	(0.000)	(0.000)
Third quintile	-0.049	-0.020	-0.040	
(upper threshold)	(0.071)	(0.341)	(0.060)	
Fourth quintile	-0.011	-0.052	0.018	
(upper threshold)	(0.825)	(0.279)	(0.636)	
Lowest quintile (Q5)	0.169***	0.064*		
(upper threshold)	(0.000)	(0.033)		
Poverty rate		-0.014***	-0.016***	
		(0.000)	(0.000)	
Q5=≤$14K			0.009	-0.006
(Low1)			(0.788)	(0.812)
Q5=$14-18K			0.051*	0.048***
(Low2)			(0.010)	(0.000)
Q5=$18-22K			0.021*	0.016
(Low3)			(0.027)	(0.150)
Median HH income				0.002
				(0.842)
White poverty rate				-0.376
				(0.084)
Black poverty rate				-0.075**
				(0.002)
Hispanic poverty rate				0.018
				(0.658)
Asian poverty rate				-0.051*
				(0.024)
White share of population				0.260
				(0.077)
Black share of population				-0.192
				(0.227)
Hispanic share of population				-0.104
				(0.063)
Asian share of population				-1.144*
				(0.015)
constant	0.909***	1.333***	1.326***	0.743***
	(0.000)	(0.000)	(0.000)	(0.000)
N	1910	1910	1910	1910
R^2	0.232	0.309	0.316	0.423

Note: State-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: County-Level Percentage Vote for Trump: Interaction with Poverty

	(5) Trump %	(6) Trump %	(7) Trump %	(8) Trump %
Top 5 % (lower threshold)	-0.016*** (0.000)	-0.008* (0.030)	-0.013*** (0.000)	-0.012*** (0.000)
Q5≤$14K (Low1)	-0.002 (0.939)	-0.019 (0.411)	-0.020 (0.250)	-0.021 (0.285)
Q5=$14-18K (Low2)	-0.062 (0.168)	-0.063 (0.117)	-0.016 (0.634)	0.030 (0.289)
Q5=$18-22K (Low3)	0.018 (0.101)	0.019* (0.037)	0.008 (0.189)	0.009 (0.118)
Low2×White poverty rate	0.145 (0.548)	0.173 (0.393)	-0.132 (0.340)	-0.231 (0.168)
Low2×Black poverty rate	0.232* (0.017)	0.214** (0.007)	0.123** (0.010)	0.101** (0.007)
Low2×Hispanic poverty rate	0.036 (0.577)	-0.006 (0.918)	-0.002 (0.964)	-0.014 (0.693)
Low2×Asian poverty rate	-0.001 (0.987)	0.001 (0.960)	0.007 (0.785)	0.004 (0.838)
Low2×Non-English speaking HHs				-0.007*** (0.001)
Median HH income	0.001 (0.914)	-0.015 (0.079)	-0.000 (0.958)	0.000 (0.974)
White poverty rate	-0.414* (0.049)	-0.329 (0.140)	-0.458* (0.018)	-0.440* (0.028)
Black poverty rate	-0.108*** (0.000)	-0.089*** (0.000)	-0.033* (0.033)	-0.033* (0.032)
Hispanic poverty rate	0.008 (0.860)	0.027 (0.503)	0.008 (0.729)	0.010 (0.674)
Asian poverty rate	-0.048* (0.015)	-0.048** (0.007)	-0.051*** (0.000)	-0.051*** (0.000)
Non-English speaking HHs (share)		-0.578 (0.159)	-0.266 (0.139)	-0.070 (0.700)
State Fixed Effects:	N	N	Y	Y
County-level Controls:	N	Y	Y	Y
N	1910	1910	1910	1910
R^2	0.430	0.550	0.781	0.785

Additional county-level controls: White, Black, Hispanic and Asian shares, Total population, Age shares, Urban share, Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: State-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: 2016 CCES Individual Voter Survey Results: Linear Probability Model

	(9) Voted for Trump	(10) Voted for Trump	(11) Voted for Trump	(12) Voted for Trump
Top 5 % (lower threshold)	-0.015*** (0.000)	-0.011*** (0.000)	-0.015*** (0.000)	-0.011*** (0.000)
Income level≤\$20K (CCES Low1 equivalent)	-0.073*** (0.000)	-0.075*** (0.000)	-0.073*** (0.000)	-0.074*** (0.000)
Income level \$20-30K (CCES Low2 equivalent)	-0.065*** (0.000)	-0.066*** (0.000)	-0.063*** (0.000)	-0.064*** (0.000)
Income level \$30-40K (CCES Low3 equivalent)	-0.041*** (0.000)	-0.041*** (0.000)	-0.028** (0.001)	-0.029** (0.001)
White×Male (WM)	-0.034** (0.004)	-0.034** (0.006)	-0.031** (0.009)	-0.029* (0.012)
WM×Low1 (WML1)	0.001 (0.955)	0.003 (0.870)		
WM×Low2 (WML2)	0.059** (0.003)	0.059** (0.003)	0.027 (0.662)	0.033 (0.584)
WM×Low3 (WML3)	0.040* (0.022)	0.039* (0.025)		
WML2×White poverty rate			-0.138 (0.785)	-0.179 (0.720)
WML2×Black poverty rate			0.413** (0.009)	0.415** (0.008)
WML2×Hispanic poverty rate			-0.281 (0.193)	-0.289 (0.183)
Black poverty rate (county-level)	-0.073 (0.070)	-0.060 (0.133)	-0.086* (0.034)	-0.073 (0.069)
Male	0.093*** (0.000)	0.092*** (0.000)	0.093*** (0.000)	0.093*** (0.000)
White	0.073*** (0.000)	0.074*** (0.000)	0.073*** (0.000)	0.073*** (0.000)
State Fixed Effects:	Y	Y	Y	Y
Individual-level Controls:	Y	Y	Y	Y
County-level Controls:	N	Y	N	Y
N	33869	33869	33869	33869
R^2	0.141	0.142	0.141	0.142

Additional individual-level controls: HH income, Black, Hispanic, Education level, Age bracket.
Additional county-level controls: Median Household income, White and Hispanic poverty rates, White, Black, Hispanic, Asian and Non-English-speaking HHs shares, Total Population, Age shares, Urban share, Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: County-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: County-Level Percentage Vote for Trump: Robustness tests

	(13) Trump %	(14) Trump %	(15) Trump %	(16) Trump %
Voter Registration	-0.055			
(share)	(0.337)			
Voter turnout		0.011		
(share)		(0.559)		
Voter participation			-0.108	
(share)			(0.237)	
Romney 2012 vote				0.900***
(share)				(0.000)
Top 5%	-0.011***	-0.012***	-0.012***	-0.006***
(lower threshold)	(0.000)	(0.000)	(0.000)	(0.000)
Q5=$14-18K	-0.025	-0.024	-0.014	0.010
(Low2)	(0.529)	(0.546)	(0.665)	(0.369)
Low2×White poverty rate	-0.039	-0.048	-0.128	-0.082
	(0.780)	(0.733)	(0.357)	(0.082)
Low2×Black poverty rate	0.112*	0.115*	0.119*	0.022
	(0.011)	(0.010)	(0.015)	(0.081)
Low2×Hispanic poverty rate	-0.002	-0.000	-0.005	-0.020
	(0.964)	(0.998)	(0.890)	(0.148)
Low2×Asian poverty rate	-0.001	-0.002	0.006	0.006
	(0.948)	(0.928)	(0.790)	(0.559)
Black poverty rate	-0.038*	-0.037*	-0.032*	-0.006
	(0.024)	(0.028)	(0.036)	(0.412)
State Fixed Effects:	Y	Y	Y	Y
County-level Controls:	Y	Y	Y	Y
N	1747	1747	1910	1632
R^2	0.778	0.777	0.782	0.975

Additional county-level controls: Low1, Low3, Median Household income, White, Hispanic, and Asian poverty rates, White, Black, Hispanic, Asian and Non-English-speaking HHs shares, Total Population, Age shares, Urban share, Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: State-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: 2016 CCES Individual Voter Survey Results: Alternative Specifications

	(17) Voted for Trump	(18) Voted for Trump	(19) Voted for Trump	(20) Voted for Trump
Romney 2012 (share of vote)				0.701*** (0.000)
Top 5 % (lower threshold, county-level)	-0.011*** (0.000)	-0.011*** (0.000)	-0.011*** (0.000)	-0.005*** (0.000)
White× Male (WM)	-0.029* (0.016)	-0.029* (0.015)	-0.038** (0.001)	-0.011 (0.231)
WM× Low1 (WML1)	0.006 (0.901)			
WML1×White poverty rate	0.452 (0.297)			
WML1×Black poverty rate	-0.030 (0.861)			
WML1×Hispanic poverty rate	-0.018 (0.925)			
WM× Low2 (WML2)				0.043 (0.321)
WML2×White poverty rate				-0.253 (0.457)
WML2×Black poverty rate				0.233* (0.041)
WML2×Hispanic poverty rate				-0.167 (0.254)
WM×Low3 (WML3)		0.052 (0.339)		
WML3×White poverty rate		-0.121 (0.786)		
WML3×Black poverty rate		-0.025 (0.869)		
WML3×Hispanic poverty rate		0.006 (0.974)		
WM×(Educ≤HS) (WMHS)			0.068 (0.071)	
WMHS×White poverty rate			-0.143 (0.651)	
WMHS×Black poverty rate			-0.070 (0.502)	
WMHS×Hispanic poverty rate			0.076 (0.553)	
State Fixed Effects:	Y	Y	Y	Y
Individual-level Controls:	Y	Y	Y	Y
County-level Controls:	Y	Y	Y	Y
N	33869	33869	33869	29889
R^2	0.142	0.142	0.142	0.566

Additional individual-level controls: HH income, Low1, Low2, Low3 (CCES equivalents), Male, White, Black, Hispanic, Education level, Age bracket.
Additional county-level controls: Low1, Low3, Median Household income, White, Hispanic, and Asian poverty rates, White, Black, Hispanic, Asian and Non-English-speaking HHs shares, Total Population, Urban share, Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: County-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: County-Level Percentage Vote for Trump: Spatial "Halo" Effects

	(21) Trump%	(22) Trump%	(23) Trump%	(24) Trump%	(25) Trump%
Top 5 % lower threshold	-0.009**	-0.011***	-0.012***	-0.007	-0.011***
	(0.006)	(0.000)	(0.000)	(0.063)	(0.000)
Median HH income	-0.036***	-0.010	-0.005	-0.020*	-0.003
	(0.000)	(0.120)	(0.543)	(0.039)	(0.685)
White share	0.202	0.162	0.216	0.199	0.127
	(0.144)	(0.247)	(0.116)	(0.091)	(0.315)
Black share	-0.594***	-0.624***	-0.507***	-0.209*	-0.603***
	(0.000)	(0.000)	(0.000)	(0.040)	(0.000)
Hispanic share	-0.278**	-0.324***	-0.298***	0.243	-0.054
	(0.002)	(0.000)	(0.000)	(0.181)	(0.406)
Asian share	-0.552	-0.692**	-0.600*	-0.223	-0.435
	(0.095)	(0.006)	(0.013)	(0.420)	(0.065)
Non-English speaking HHs, 2009				-0.767***	-0.539***
(share of population)				(0.000)	(0.000)
Non-English speaking HHs, 2016	-0.522	-0.324	-0.382	0.143	0.290
(share of population)	(0.320)	(0.177)	(0.079)	(0.803)	(0.254)
"Halo" variables: maximum value in neighboring counties within a 50-mile radius					
Halo Top 5%	-0.003	-0.004**	-0.002*	-0.002	-0.002*
	(0.067)	(0.003)	(0.031)	(0.208)	(0.026)
Halo White share	0.028	0.075			
	(0.633)	(0.151)			
Halo Black share	0.302***	0.088***			
	(0.000)	(0.001)			
Halo Hispanic share	0.268***	0.056			
	(0.000)	(0.239)			
Halo Asian share	-0.127	0.081			
	(0.246)	(0.426)			
Halo Non-English speakining HHs			0.201	0.737***	0.277
(share)			(0.221)	(0.000)	(0.066)
State Fixed Effects:	N	Y	Y	N	Y
County-level Controls:	Y	Y	Y	Y	Y
N	1815	1815	1843	1843	1843
R^2	0.617	0.793	0.787	0.573	0.796

Additional county-level controls: White, Hispanic, and Asian poverty rates, White, Black, Hispanic, Asian pop. shares, Total Population, Age shares, Urban share Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: State-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: CCES Individual-level Spatial "Halo" Effects

	(26) Voted for Trump	(27) Voted for Trump	(28) Voted for Trump	(29) Voted for Trump	(30) Voted for Trump	(31) Voted for Trump
Sample:	Whites	Whites	Whites	Full	Full	Full
Top 5% (county-level)	-0.012*** (0.000)	-0.011*** (0.000)	-0.011*** (0.000)	-0.012*** (0.000)	-0.011*** (0.000)	-0.010*** (0.000)
White share (2016, county-level)	0.544*** (0.000)	0.461*** (0.000)	0.170 (0.312)	0.409*** (0.000)	0.377*** (0.000)	0.275*** (0.000)
Black share (2016, county-level)	0.433*** (0.000)	0.253* (0.035)	1.832** (0.003)	0.506*** (0.000)	0.191* (0.035)	0.087 (0.327)
Hispanic share (2016, county-level)	0.182* (0.011)	0.060 (0.439)	1.390 (0.151)	0.158*** (0.001)	-0.015 (0.806)	0.158 (0.063)
Non-English speaking HHs (2016 share, county-level)	-0.001 (0.654)	0.000 (0.998)	0.001 (0.657)	-0.003 (0.140)	0.001 (0.801)	0.009* (0.014)
White share (2010, county-level)			0.397 (0.078)			
Black share (2010, county-level)			-1.477* (0.020)			
Hispanic share (2010, county-level)			-1.053 (0.308)			
Non-English speaking HHs (2009 share, county-level)						-0.466** (0.003)
"Halo" variables: maximum value in neighboring counties within a 50-mile radius						
Halo top 5% (county-level)	-0.007*** (0.000)	-0.007*** (0.000)	-0.007*** (0.000)	-0.006*** (0.000)	-0.005*** (0.001)	-0.005*** (0.000)
Halo White share (2016, county-level)	-0.206** (0.007)	-0.158 (0.064)	-0.177* (0.030)			
Halo Black share (2016, county-level)	0.241*** (0.000)	0.098** (0.007)	0.079* (0.031)			
Halo Hispanic share (2016, county-level)	0.102* (0.014)	0.046 (0.284)	0.036 (0.389)			
Halo non-English speaking HHs (2016, county-level share)				0.388** (0.001)	0.248 (0.054)	0.302* (0.016)
State Fixed Effects:	N	Y	Y	N	Y	Y
Individual-level Controls:	Y	Y	Y	Y	Y	Y
County-level Controls:	Y	Y	Y	Y	Y	Y
N	26230	26230	26230	33869	33869	33869
R^2	0.088	0.095	0.096	0.132	0.141	0.141

Additional individual-level controls: HH income, Male, White, Black, Hispanic, Education level, Age bracket.
Additional county-level controls: Median Household income, White, Black and Hispanic poverty rates, Total Population,Urban share, Unemployment, Male LFPR, China shock, Manufacturing and Mining shares of employment.

Full results available in the Online Appendix.

NOTE: County-level cluster-robust p-values in parentheses: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$