The Diversity Wave:
A meta-analysis of ethnic diversity, perceived threat and native white backlash

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**Abstract.** Does ethnic diversity increase or reduce white threat perceptions? Social scientists continue to devote considerable effort to investigating the effects of rising ethnic diversity on intergroup relations. In this paper we report findings from a meta-analysis of studies of the effects of ethnic context on opposition to immigration and support for the radical right. Our analysis is based on 183 studies, averaging 25,000 observations each - a knowledge base of over 5 million data points. We find support for both contact and threat theory, with each operating at distinct geographic levels. This reveals that the association between diversity and threat shifts in nonlinear fashion as we increase the size of contextual unit. The resulting cubic curve sees threat responses crest at the smallest and largest geographies, whereas in units of 5,000-50,000 people (such as wards or tracts) greater diversity is associated with reduced native white threat perceptions. This nonlinear 'wave' relationship holds equally across the domains of support for anti-immigrant parties, opposition to immigration and generalized mistrust. This work adjudicates between, and recasts, the current linear, zero-sum understanding of the diversity-threat relationship.

How does rising ethnic diversity in the West affect perceptions of threat among native-born white majorities? In the social sciences there is now a vast and expanding body of research on how the surrounding ethnic context –whether at the local, regional or national level- impacts upon majority perceptions and behaviour. Following Hirschman’s Exit, Voice and Loyalty (1970), one may distinguish two streams of research in this area, one concentrating on white ‘exit’ in response to rising diversity (i.e. reduced trust and willingness to share resources), the other on white ‘voice’, or political resistance to ethnic change.

Work on voice, in the form of anti-black prejudice and politics, has a long scholarly pedigree (i.e. Key 1949). Yet white exit has arguably received more attention following a controversial paper published nearly ten years ago in which Robert Putnam (2007) suggested that rising immigration and ethnic diversity –at least in the short-term- tends to reduce social solidarity. Drawing on findings from a large nationwide survey in the United States, Putnam argued that in more ethnically diverse census tracts citizens ‘hunker down’ –they feel threatened by ethnic change, withdraw from collective life and become less trusting of their neighbours (also Alesina and La Ferrara 2002). The debate about the impact of ethnic context on white exit continues and remains unresolved. For instance, Putnam’s claims about the short-term negative effects of diversity clash with those whose research appears to highlight the positive effects of intergroup contact in small-scale contexts (Pettigrew and Tropp 2006; Stolle et al. 2008).
Exit, in the form of white withdrawal from community and solidarity under conditions of increased ethnic diversity, has received meta analytic treatment (van der Meer and Tolsma 2014). Our main contribution to knowledge is to therefore redress the balance by undertaking a meta-analysis of work on white ‘voice’: specifically, attitudinal opposition to immigration and voting for populist radical right parties that oppose rising diversity (see Mudde 2007). While there are already several helpful reviews of the political science subfields of public attitudes toward immigration and diversity (Ceobanu & Escandell 2010; Hainmueller & Hopkins 2014), and support for the anti-immigrant radical right (Meindert & Fennema 2007; Rydgren 2007), in this paper we contribute by conducting a formal meta-analysis, akin to those for the fields of diversity and social solidarity (van der Meer and Tolsma 2014) and contact theory (Pettigrew and Tropp 2006). We return to the question of ‘white exit’ toward the end of the paper where we suggest that our voice-based model also applies to generalized mistrust, a form of white exit.

We argue that the field needs to move beyond the zero-sum debate between contact and threat theory. Our metadata shows that both theories fit the data, but do so at different geographic levels. Our second contribution to scholarship is therefore to pay closer attention to the size of the context in which diversity occurs. A notable advance in the literature on exit and voice has been an attention to the way geographic scale moderates the diversity-threat relationship. Rather than a linear conception of the diversity-threat nexus – in the direction of threat or contact - our results reveal how context size acts as a moderating lens. That is, the effect of diversity on threat rises and falls in a systematic,
wavelike way as we vary the size of unit under consideration. What geographers refer to as the modifiable areal unit problem (MAUP) forms the centrepiece of our analysis.

Contact, Micro-Threat and Macro-Threat

Threat theory (i.e. Putnam 2007) and contact theory (i.e. Allport 1954) set the parameters of our interpretive framework. Within threat theory, however, we distinguish between micro- and macro-threat. A number of scholars have suggested that contact effects are more likely in smaller geographies than larger units. This is because individuals in diverse locales are able to meet minorities in person, challenging fears or misperceptions, whereas at the city or county level – especially if highly segregated - the modal white person experiences only limited inter-ethnic contact (Kaufmann and Harris 2015: 1566; Schlueter and Scheepers 2010: 293). Meanwhile, political contestation increases in larger units (Ha 2010: 30). This macro-threat argument intimates that geography moderates the diversity-threat relationship in linear fashion: as the size of unit increases, the effect of increased ethnic diversity shifts from reducing to enhancing perceptions of threat among native whites. More recently, people. We surmise that there are distinct forms of threat operating at each end of the scale.

By contrast, Dinesen and Sonderskov (2015: 553-54) point to psychological research which suggests co-ethnics tend to trust each other more than members of out-groups. At close quarters,
diversity may prompt greater unease among white residents than it may at larger scales. Biggs and Knauss (2012) and Kawalerowicz (2016) find, using a membership list for an anti-immigration radical right party in Britain, that whites in relatively diverse Output Areas (average population 300) are more likely to be party members than whites in homogeneous Output Areas. The micro-threat claim appears to run counter to both contact and macro-threat perspectives.

**Approach**

Our meta-analysis encompasses a quantitative analysis of all work we could find on ethnic diversity and how it relates to immigration attitudes and support for the anti-immigration radical right. We restrict our meta-analysis to studies published since 1995, a period that has witnessed considerable demographic change across much of the Western world. By undertaking a meta-analysis of the role of ethnic context in anti-immigration mobilization we compare individual papers in a systematic, measurable and rigorous manner.

Our analysis extends much further than past reviews by encompassing 5 million data points. Articles based on particular datasets may repeatedly uncover similar relationships but it is only by considering the full range of studies that larger patterns may emerge. The meta-analysis reveals a macro-level relationship between geographic context size and ethnic threat that would be difficult to discern from a single dataset or wide knowledge of the literature. This is because any one study
examines, at most, two or three geographic levels. In this paper we survey a finer-grained sweep of geographic context sizes to ask how modifying the areal unit affects the key association between ethnic diversity and measures of ethnic threat.

Our main finding is an important nonlinear relationship between the size of the ethno-contextual unit and ethnic threat which takes a cubic polynomial pattern. This pattern sees white threat responses to diversity crest at the smallest (<1000) and largest (national) geographies but in units of 5,000-50,000 people (such as wards or tracts) greater diversity is associated with reduced threat perceptions. This nonlinear relationship holds equally across the threat domains of attitudinal opposition to immigration and minorities, electoral support for the radical right and generalized trust. This adjudicates between, and recasts, the currently linear understanding of the diversity-threat relationship. We also claim that whereas diversity levels display nonlinear effects ethnic change almost always predicts heightened threat. Finally, this work seeks to focus the field, pointing to specifications which all studies should apply before highlighting areas most in need of further research. In the next section we provide an overview of existing research. We then present the results of our meta-analysis and conclude by discussing their implications for the study of the contextual effects of diversity on native white ‘voice.’
There is now a vast literature that examines the relationship between the surrounding ethnic context and public attitudes toward diversity and immigration. A large subfield of research on the political effects of rising ethnic diversity has also emerged, notably the relationship between ethnic context and public support for anti-immigrant radical right parties (for a full list of studies that were included in our meta-analysis see Appendix 1). Overall, 80% of our sample is comprised of published articles or books and 20% are working papers or dissertations. We consider work from the post-1995 period but there is a strong skew toward the present, with half of all studies dating from 2011 and just 3% from 2000 or earlier. Much of the quantitative work on immigration and the populist radical right is thus of recent vintage. Had we focused on native minorities (i.e. white-black dynamics in the United States), where there is a longer tradition of scholarship, the average year of publication would fall considerably earlier.

Our data consist of 558 reported results from multivariate models published in 183 studies that examine the effects of ethnic context on public attitudes toward immigration, public support for anti-immigration parties, and social cohesion measures. We sought to exhaustively include all relevant articles and books, as well as theses and working papers, that explore the role of ethnic context in public attitudes toward a) immigration, immigrants or immigrant-origin minorities, or b) support for the populist radical right. Further, we include small random samples of studies featuring
cognate independent (% native minorities) and dependent (trust, cohesion) variables for comparative purposes. In the latter case, the aim is exploratory rather than exhaustive, as for the anti-immigration and radical right literatures. [We exclude studies focusing on the extent of intergroup contact as this outcome is mathematically related to contextual diversity.] Since we have largely avoided the literature on diversity and trust/cohesion, we are able to conduct a robustness test which involves re-analyzing data from a recent meta-analysis of the literature on contextual effects and solidarity (Van der Meer and Tolsma 2014). Only two studies we examine were also considered by the van der Meer et. al. study. Further details on our sampling strategy and inclusion rules may be found in Appendix 1.

The studies we analyse deploy variables drawn from various datasets, applying a variety of methods to distinct sets of countries and time periods. This introduces heterogeneity which may obscure ‘universal’ relationships. Even with a significant general relationship between ethnic diversity and threat at the p<.05 level, there is still a 5 percent chance any given study will fail to find a significant effect. Our work helps to surmount such problems by amassing 183 articles averaging 25,000 observations each, resulting in a knowledge base of over 5 million data points. Our meta-model reflects a ‘wisdom of crowds’ philosophy in which the average of many viewpoints offers a prediction nearly as good as the best individual result. This is because knowledge in a complex system such as a market or academic discipline is distributed rather than centralised, and thus benefits from being aggregated (Surowiecki 2004; Schmidt and Hunter 2015). Accordingly, we harness an unprecedented quantity of accumulated social scientific insight to derive average effects and emergent
properties. None of this obviates the need for further country-level and comparative research: meta-relationships change between countries and over time while new studies contribute fresh questions, data and methods.

We consider 187 studies. Leaving aside four studies that focus on minorities’ attitudes to outgroups, 39 of 183 studies, or 21.3%, examine support for the populist radical right. A further 133, or 72.7%, focus on attitudes to immigration. Three consider attitudes to native minorities such as African-Americans or Jews and a further 9 (5 percent) model the effect of ethnic context on trust or social cohesion. The latter are included for comparative purposes only, and are not intended to be exhaustive. Table 1 in Appendix 2 provides a regional breakdown of studies. Two kinds of work dominate the field. More than half consist of single-country studies from Europe (39%) and North America (20%) using ethnic data for sub-national units. Most others involve cross-national comparative work on Europe: 37% are cross-European - though some are restricted to the Western (6%) or Eastern (0.5%) part of the continent. A further eight papers (4.3%) adopt a global purview, including two studies focused on non-European cases (Japan and South Africa) and one on New Zealand. European single-country work has been dominated by work on Britain (17), the Netherlands (20) and Belgium (8), which comprise almost two-thirds of single-country studies in Europe. The United States accounts for the largest single number of country studies (31), with a further five papers focusing on Canada.
Turning to data, one quarter of studies use the European Social Survey (ESS), rising to two-thirds for those focused on comparative European work. Most of the remainder rely on the Eurobarometer (12 of 67 studies), European Values Survey (6 studies) or International Social Survey Programme (2 studies). The General Social Survey (GSS) is less dominant among American papers. Only 28% use it, 9% utilize the Citizenship, Involvement, Democracy (CID) Survey, 6% the National Election Study (ANES) with the rest spread across fifteen other datasets. Elsewhere, 4 of 5 Canadian papers use the Canadian Election Study and 4 of 21 British articles the British Election Study.

In terms of unit of analysis, while cross-national comparisons occasionally drill down to region or locale, most (56 of 67 cross-national studies) draw on country-level contextual data. Importantly, studies of the largest ethnic contexts (i.e. countries) are more vulnerable than other levels to unit effects: countries vary for historical, cultural, economic and political reasons much more than sub-units of countries do. Failing to account for this step-change when examining how geographic scale moderates the diversity-threat relationship may result in bias.

We felt it important not to exclude purely aggregate models – usually ecological regressions of electoral support for the populist radical right on census data. These, which form just under 12% of the total, did not produce results markedly different from those obtained with individual data, with the important proviso that aggregate results elide ethno-contextual and ethno-compositional drivers of populist right support (i.e. is far right support lower in diverse wards because minorities don’t back
such parties or because of contact effects on whites?). The remainder are comprised of studies of individual-level responses attached to contextual data, such as the share of minorities in a district.

Among the studies we uncovered, just 14% are multilevel: that is, they measure diversity in more than one geographic context (i.e. tract and county minority share). We argue that researchers should, wherever possible, incorporate more than one level of ethnic context because our work suggests diversity has disparate effects on white threat perceptions at different geographic scales.

Current practice also falls short when it comes to case selection. Just 37% of studies restricted their samples to native-born white respondents while 62% included all respondents in their analyses. While two-thirds of North American studies are restricted to native whites, this is true of just 41% of European single-country studies and 25% of European multi-country studies. Why is this problematic? As the proportion of minorities in a contextual unit rises, the likelihood that a respondent living in the unit is an ethnic minority increases. This dampens minority threat effects because minorities usually support immigration more than native whites. Though many studies not restricted to native whites include terms for ethnicity and nativity in their models, this approach only works if these individual attributes are interacted with ethnic context. Given that part of the field’s aim is to understand white responses to immigration, and minority samples are in any case often too small to properly interrogate minority attitudes, results for native-born whites should be reported separately. Needless to say we find stronger effects – in the direction of both threat and contact - in samples that are restricted to native-born whites.
As stated at the outset, a major line of inquiry in the literature has been to test for the effect of ethnic diversity on threat perceptions, with studies often producing mixed results. Whereas some find a positive relationship between perceived threat and ethnic diversity, others suggest that increased intergroup contact produced by higher diversity reduces native white threat.

One useful way forward is to examine the properties of studies that seek to moderate the diversity-threat relationship. What are the attributes of studies reporting a positive diversity-threat association? Or, conversely, what kinds of studies find that increased diversity reduces white threat? This is our main research question. The key dependent variable is *diversity threat*, the level of diversity-driven threat, which is derived from the coefficient reported in each model of each paper. Source coefficients measure the relationship between an ethno-contextual independent variable (i.e. the percentage of minorities in a given unit) and a threat outcome variable (i.e. the level of public opposition to immigration or support for the populist radical right). The simplest formulation of the dependent variable is a dummy for diversity-driven threat-enhancement (1) vs. diversity-driven threat-reduction (0). This is based on the sign of the coefficient (+ or -) reported, regardless of statistical significance.

A positive relationship signifies a threat response to diversity and a negative association a contact effect.¹
We also test two other variants of the dependent variable that capture more of the variation in the outcome of interest, diversity threat. We first model a seven-category variable ranging from +3 through -3 distinguishing significant studies at the p<.05 level, coded 1 or -1, and at the p< .01 (2 or -2) or p< .001 (3 or -3) levels. This censors the full range of values, so in a subsequent step we use the coefficient/standard error ratio (equivalent to t-statistic or, for aggregate studies with continuous dependent variables, z-score) to derive a standardised measure of weight of evidence, i.e. the importance of a particular variable in moderating the diversity-threat relationship. For the 11 odds ratio or probit studies, we assign a standardized coefficient of 2 for results at the p<.05 level, 3 for p<.01 and 5 for significance at the p<.001 level. Insignificant coefficients are assigned a zero. This captures most of the variation in diversity threat but at the expense of increased error caused either by different methods and response scales, or by the imperfect matching of weight of evidence scores between studies reporting coefficients and the 11 studies reporting odds ratios or probit coefficients.

No single measure is superior but each tells a similar story: together, they assemble a consistent portrait of the correlates of diversity threat.

*Independent variables*

We code for the following variables: year of study; number of observations; whether the model contains a term for the economic deprivation/wealth of the contextual unit; multilevel analysis (i.e.
whether the study contains ethno-contextual coefficients at more than one geographic level);

aggregate or individual-level data (whether the dependent variable is an individual response or a
district mean, such as the share of the vote for the populist radical right); dataset used; and attitude
controls - whether the model includes attitudinal parameters such as ideology, authoritarianism or
partisanship.

We also record the population size of the contextual units, recoded into 9 categories. These
run from category 1 for micro geographies such as residential blocks, which contain fewer than 1000
people, to 9, for country. We use categories because the number of people per unit is not normally
distributed, i.e. a small number of wards, counties or metropolitan areas are very large and many are
quite small. Papers usually do not provide the modal population for the contextual units they use thus
we do our best to approximate unit size from information in the article and external sources. We also
include a quadratic and cubic term for unit size to capture nonlinear effects at the lowest and highest
geographic levels. If the relationship between diversity level and threat is a straight slope regardless of
unit size, these terms will not be significant. However, if the relationship rises and falls as unit size
increases, the coefficient of these variables will be significant and change their sign with as we
modify the areal unit.

In addition, we include dummy variables for papers that use longitudinal data; measuring
ethnic change rather than the overall level; contain a dependent variable referring to ‘immigration’
rather than ‘immigrants’; and ask for opinion positively (i.e. ‘do immigrants bring benefits?’) or
negatively (‘do they bring costs’). We also code for studies reporting log odds, tobit or probit results as these coefficients are less easily compared to logistic or linear regression coefficients. We focus only on main effects and thus exclude coefficients for interactions between ethnic composition and other variables (i.e. diversity x authoritarianism or unemployment). Finally, studies are assigned a world region as follows: Western Europe single-country studies, West European multi-country studies, North America, Europe-wide multi-country studies, Eastern European multi-country studies, global multi-country studies, non-Western single-country studies (Japan, South Africa), and Australia/New Zealand.

**Threat or Contact: where does the preponderance lie?**

We begin by reporting ethno-contextual coefficients from studies of opposition to immigration/support for the radical right, irrespective of whether they are statistically significant. Science is biased toward reporting statistically-significant findings (Easterbrook et. al. 1991; Franco et al. 2014) yet null results may be vital for providing a fuller picture of the phenomena under investigation. With this in mind, 59.5% of 570 model coefficients report that diversity is positively associated with threat and 40.5% that it is negatively associated with it. Does this suggest, as Putnam (2007) did, that most research finds that ethnic diversity increases perceived threat? This is a matter of interpretation. The balance of tests leans in favour of diversity-threat. However, just 186 of 570
(32.5%) coefficients show a statistically significant (p<.05) threat effect – 35.7% if the criteria are relaxed to include results significant at the p<.1 level. This means that most models do not find a statistically significant threat effect from contextual diversity.

There are, however, important reasons to believe that threat effects brook larger than contact effects. One of the most robust and consistent findings in our data is that statistically-significant relationships between diversity and threat tend to be positive. As noted above, almost 60% of ethno-contextual coefficients report diversity threat. When we restrict our purview to the 257 ethnic context coefficients which are statistically significant predictors of threat, the balance shifts from 60-40 to 72-28 in favour of threat enhancement over abatement. If one views null findings as noise, then Putnam (2007) was correct, with our meta-analysis of the literature supporting a threat interpretation. The take-home message is clearly different if the reader considers that null findings refute Putnam’s thesis.

The results reject a blanket version of the contact hypothesis - that is, one in which diversity at all geographic levels is expected to produce favourable public attitudes to immigration, immigrants and minorities. Yet we also reject a universal threat argument. Diversity is associated with reduced threat at certain geographic levels. Indeed, our main point is that both threat and contact theories are valid in their respective geographic spheres. Consequently, our next step is to undertake a more forensic analysis of how geography moderates the diversity-threat relationship. In the next section we show how threat or contact responses are sensitive to the size of the areal unit in which diversity is
found, but not in a straightforward way. We deliberately refrain from setting out hypotheses, preferring to allow regularities to emerge from our analysis.

**Results**

Recall that the dependent variable takes three forms - a logistic regression for threat increase/decrease, an ordered logit for the size of contextual effect on threat decrease/increase based on p value (ranging from -3 to +3), and a linear regression based on the standardized coefficient of the diversity-threat association (from -8.7 to +12.3). All can be interpreted as asking: which types of studies find threat effects and which report contact effects? In other words, what characteristics of studies account for variation in the association between diversity and threat between studies? The models we present test for whether particular features of the studies in our dataset are associated with diversity threat.

Before addressing significant findings, note the variables we expected to play a significant role which do not. Many null results are displayed in Appendix 2. These include the type of dependent variable (immigration attitudes, support for the populist radical right, trust); year of study; as well as dummy variables for multilevel model and aggregate (ecological) analysis. Other parameters which failed to explain variation in the diversity-threat relationship between studies include: whether deprivation controls were used at the contextual level; the presence of attitudinal predictors at the individual level; the wording of the dependent variable (i.e. immigrants rather than immigration,
positive versus negatively-worded questions); and subjective (versus objective) measures of diversity.

This is surprising as including a term for contextual deprivation (i.e. unemployment rate) might be expected to weaken the coefficient for ethnic diversity (i.e. threat effects). Including attitudinal data on ideology or issue positions might also be expected to lessen the impact of diversity effects on threat compared to studies that do not include these. Outcome variables worded as opinion of ‘immigrants’ rather than the more impersonal ‘immigration’ also did not elicit significantly lower threat, contrary, again, to expectations. The total number of cases (N) and dataset used similarly did not account for variation in threat/contact outcomes between studies.

Critically, there was no significant difference in the diversity-threat relationship when threat was measured as support for anti-immigration populist radical right parties, anti-immigration attitudes, animosity toward outgroups or generalized mistrust. This is a very important result for two reasons. First, it lends credence to the arguments of those (e.g. Mudde 2007) who view support for the populist radical right as being motivated by the immigration issue rather than economic pessimism or a general dissatisfaction with mainstream politics. Second, there are important connections between the way immigration sentiment, voting for the radical right and trust link to diversity. This offers justification for a wider use of threat theory to understand these distinct empirical phenomena. We only examine eight studies (23 model coefficients) of trust and social cohesion, so this finding should be considered provisional. However, we will later show how our cubic wave model also fits trust data, albeit in a modified way.
Finally, diversity tends to have a smaller standardized effect on threat than the most robust socio-demographic variables such as age or education, not to mention proximal attitudes such as partisanship and ideology. Only in studies where diversity has its strongest positive association with threat does it register an weight of evidence score larger than age (Schlueter and Davidov 2013: 186), education (Kessler and Freeman 2011:276-78) or party identification (Newman and Johnson 2012: 34).

Model

What variables significantly predict diversity threat? In the final column of Table 2 in Appendix 2, the variable ‘significant’ tells us that when a diversity coefficient is significantly associated with threat, this is more often in the direction of increasing rather than reducing it. The predicted probability of a threat result, with other variables held at their mean, rises from .55 to .72 when a diversity coefficient moves from insignificance to significance at the p<.05 level. When run as a linear regression (on the standardized coefficient of the reported diversity-threat relationship), the size of the threat coefficient increases from .21 when a diversity coefficient is reported not significant to 1.43 when returned as significant at the p<.05 level. A standardized coefficient of 1.43 is approximately equivalent to significance at the p<.1 level. This reinforces our earlier observation that *significant* diversity-threat relationships usually confirm threat rather than contact theory. Having said
this, we shall see that the relationship is not linear: under certain conditions, greater diversity is
associated with significantly lower white threat.

Size of Unit

The key to the nonlinearity argument is unit size. As shown in Table 2 in the Appendix 2, the
size of the geographic unit in which contextual diversity is measured does not predict a significant
linear increase or decrease in threat. Van der Meer and Tolsma (2014) report a similar finding for
work on trust and cohesion. But what if the relationship is nonlinear? Figure 1 summarises the share
of studies reporting a positive diversity-threat relationship for each category of contextual unit size.
The way geography moderates the diversity-threat relationship assumes a cubic polynomial shape, a
kind of ‘DNA’ of the diversity-threat relationship.

In Figure 1, based on our dataset of 558 coefficients from 183 studies, a threat response is
reported for 12 of 14 (85.7%) model coefficients when diversity is located in units of less than 1,000
people. Net threat falls rapidly as units increase in size to those with populations of between 1,000-
5,000 people. At slightly larger units of between 5,000-10,000, higher levels of diversity predict lower
threat perceptions almost 60% of the time. However, beyond units of 50,000, threat again dominates
(53.8% of coefficients), peaking at units of 100,000-500,000 people before declining somewhat to
63.7% in the largest geographical unit, namely the country.
The cubic wave pattern becomes even more pronounced when we restrict our analysis to studies of native-born whites reporting statistically-significant findings. Figure 2 presents the overall patterns in threat responses to diversity when the sample is restricted to native-born whites.
Figure 2.

Weighting the data

Across the 183 studies each ethno-contextual coefficient in each model is treated as a separate observation. For example, a study that presents five models, each of which tests for the effect of the percentage share of immigrants and minorities in a geographic unit would yield ten coefficients, or ten rows of data out of the 570 in our dataset. If, alternatively, the percentage share of immigrants and minorities are tested at two geographic levels, i.e. tract and county, then this produces twenty coefficients. A small number of the papers we include do this, hence one of our articles furnishes 18 coefficients out of 570. A third of studies add 9 or more records to our data. At the other end of the
scale, half the papers contribute 4 or fewer ethnic context coefficients and 30 percent just 1 or 2. Since
the number of coefficients per paper ranges from 1 to 18, we include a frequency weight which we
apply in some of our models in order to accord each study equal representation. This ensures a
maximum diversity of viewpoints across the discipline, in line with the wisdom of crowds concept.

Figure 3, which restricts our sample to studies focusing only on native-born whites and excludes coefficients failing to reach statistical significance, embodies this weighting scheme. Each of
the coefficients are inflated by a factor of between 1 (10x) and 18 (180x) in order to account for the
fact that the least-represented studies contain just one model coefficient while the maximum are
represented by 18. The cubic wave remains pronounced, as shown by the dotted line, a 3rd-order
polynomial curve (of the form $y = a+bx+bx^2+bx^3$) whose components we model shortly. Overall,
threat effects predominate over contact effects, but when ethnic contexts fall within the lower-middle
range (i.e. 1,000-50,000 population), contact and threat results are finely balanced. We would go
further and argue that in the lower-middle range, with additional controls, contact effects
predominate.
Ethnic Levels vs. Ethnic Change

The findings presented in Figure 3 suggest that in studies restricted to native white respondents which report significant coefficients, the balance at all levels supports threat theory. While this appears to be so even in the 5,000-50,000 unit size range, support for the threat hypothesis drops substantially when a term for the rate of ethnic change is included. Now, for the 5-50k range (50-100k in the weighted data), there is just as good a chance a study with a significant diversity coefficient will report a threat-abatement effect as a threat-enhancing relationship. One interpretation is that in this range there is an absence of threat but no evidence for a contact effect. The other view, however, which we incline towards, is that there is a heterogeneous effect, with diversity prompting
contact in some cases and threat in others. In this manner, we believe contact theory is a plausible explanation for the decline in diversity threat observed in the lower-middle part of the geographic distribution.

Returning to our ethnic change finding, it is noteworthy that for 13 statistically-significant ethnic context coefficients measuring ethnic changes rather than levels for units in the lower-middle size range, fully 12 (93%) display a threat effect. Even if we include insignificant studies, 80% of 25 coefficients in this geographic range are signed in the direction of diversity threat. In many models where change coefficients indicate diversity threat, at least some of the coefficients for minority levels are signed in the opposite direction, signifying a cross-cutting dynamic in which higher levels of diversity produce contact while fast change prompts threat (Havekes 2014; Havekes et. al. 2014; Kaufmann 2016; Tolsma et. al. 2008; Walker and Leitner 2014). We surmise that including a coefficient for ethnic change would shift the weight of evidence of studies in the lower middle range from threat toward contact. Future scholarship should include a coefficient for both levels and changes where possible, though the analyst must be mindful of collinearity between the two measures as past minority inflows constitute contemporary levels of diversity.

A final aspect to consider regarding levels and changes is the role of longitudinal data. Longitudinal studies in our dataset measure the effect of ethnic change on changes in attitudes, voting or trust. For instance, 71% of 93 coefficients measuring the effect of ethnic changes on levels of threat show a positive relationship. In similar fashion, longitudinal studies measuring the effect of ethnic
change on changes in threat find that 27 of 31 coefficients (87%) show a positive effect. Both measures tap ethnic shifts rather than historic levels of ethnic diversity, and this increase in diversity is what seems most related to opposition to immigration. For modelling purposes we combine ethnic change and longitudinal studies into a single dummy variable. Diversity levels are of course strongly tied to changes in diversity. Yet the two are not identical: longstanding native minorities may cluster in certain areas such as northern New Mexico, while areas little affected by immigration may receive a sudden surge of newcomers, as in Boston, England, or in Hispanic 'new destinations' in the Southeastern US in the 2000s (Frey 2015).

Longitudinal data is also important because fixed-effects models filter time-invariant characteristics of geographic units. These play an outsized role in larger units such as nations, whose unique cultural values and historical institutions may be confounded with variables of interest such as diversity. For instance, the liberal political cultures of Canada and Sweden help explain both their levels of ethnic diversity and their citizens’ relatively liberal attitudes to immigration. A cross-sectional model of the impact of national diversity on immigration attitudes blends the cross-cutting effects of political culture and diversity threat, obscuring underlying relationships. Ethnically diverse Sweden appears more accepting than ethnically homogeneous Japan but it is Swedish culture and history, not its diversity, which may be driving the relationship. By contrast, a model tracing how immigration attitudes change over time within a country as diversity increases is less subject to error.
Comparing the diverse Sweden of today with its more homogeneous incarnation of twenty years ago is better than comparing it to homogeneous Japan (Gallego et. al. 2016).

The lack of repeated measures in most large-scale surveys helps explain the relative paucity of longitudinal studies. A few longitudinal datasets on voting exist and some researchers have compiled pseudo-cohort or aggregate panel data.¹ Most are at country level as aggregating individual data into national panels is much more feasible than tracking diversity and threat perceptions over time in smaller units. Indeed, with the exception of Laurence and Bentley’s (2015) ward-level fixed effects model of social trust in Britain (using BHPS/UKHLS), all longitudinal studies we could find (31 coefficients) take country as the unit of analysis (Coenders et. al. 2008; Hatton 2014; Davis and Deole 2015; Ziller 2014). Regardless of unit size, when it comes to assessing the impact of diversity on threat, it is abundantly clear that more longitudinal work is needed.

Models of Diversity Threat

Having eliminated most candidate variables from our dataset, we focus on the size of geographic unit and ethnic change. Geographic unit size clearly moderates the diversity-threat relationship. Figures 4a through 4h show the relationship for different samples of the data, overlaid with a third-order polynomial curve. The first row of graphs chart, along the dimensions of context size and threat

¹ For example Britain’s BHPS/UKHLS
effect, all reported diversity coefficients in the dataset less those specifically concerned with minority attitudes to immigration (N=558 coefficients). The second restricts the data to studies focusing only on native whites which report significant results (N=118 diversity coefficients). The third presents a weighted version of the previous dataset (N=118), with studies that are underrepresented in terms of reported diversity coefficients inflated to the same level as studies with the heaviest representation (18 coefficients) in the data. In other words, if a study only conducted one test of the effect of contextual diversity, we assume this was run in a further 17 models with an identical result.

The first graph in each row shows the linear equation. This takes the form $y = b + a(x)$, where $y$ is the proportion of coefficients reporting a threat effect and $x$ the geographic unit category, from 1 to 9. The linear equation fits the data relatively poorly, much as van der Meer and Tolsma (2014) reported. The second graph in each row displays the second-order (squared geography size) polynomials. A quadratic based on a squared geographic term, $y = b - a(x) + b(x^2)$, substantially improves fit. The final graphs show the third order (cubed geography size) polynomials. With the cubic term, fit improves once again, and the equation now takes its characteristic cubic form $y = a - b(x) + b(x^2) - b(x^3)$. 
Recall the three forms of our dependent variable: a dummy for threat enhancement (1) or reduction (0); a modified seven-category standardized coefficient based on significance level (+3 to -3); and a pseudo-standardized coefficient (-8.7 to +12.3). Table 1 begins with a logistic regression of the threat dummy variable on our main predictor variables, including diversity coefficients which our source studies report as not significantly associated with threat. Model 1 shows that geographic unit size (on a 1-9 scale) is of only borderline significance as a predictor of a diversity-threat association.

In Model 2, which adds a quadratic term for geographic unit size, we see that none of the geographic predictors are significant but the signs of the variables point in the expected direction. In Model 3 we introduce a cubic term for geographic unit size. This increases model power substantially. The three
geographic terms are all significant and now reflect the pattern shown in Figures 4 a – h. Adding a parameter for ethnic change (including longitudinal studies) in Model 4 almost doubles the model fit. Year fixed effects (model 5) have a similar impact. Weighting the data to equalize the number of coefficients per study – as we have in the final model in the table – leads to a large inflation of sample size. This biases error terms downward so less attention should be paid to comparing absolute coefficients and error terms with preceding models. The key point is that the relative effect sizes among the coefficients remains similar between the weighted and unweighted (model 5) data in the last two columns.

Table 1. Models of Positive Diversity- Threat Association (Including Insignificant Coefficients)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographic Size</td>
<td>.062</td>
<td>-.227</td>
<td>-2.869***</td>
<td>-3.002***</td>
<td>-3.058***</td>
<td>-1.621***</td>
</tr>
<tr>
<td></td>
<td>(.034)</td>
<td>(.196)</td>
<td>(.750)</td>
<td>(.747)</td>
<td>(.805)</td>
<td>(.100)</td>
</tr>
<tr>
<td>Geography squared</td>
<td>.025</td>
<td>.585***</td>
<td>.617***</td>
<td>.618***</td>
<td>.306***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.017)</td>
<td>(.151)</td>
<td>(.151)</td>
<td>(.164)</td>
<td>(.020)</td>
<td></td>
</tr>
<tr>
<td>Geography cubed</td>
<td>-.035***</td>
<td>-.037***</td>
<td>-.036***</td>
<td>-.017***</td>
<td>.577***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.010)</td>
<td>(.010)</td>
<td>(.035)</td>
<td></td>
</tr>
<tr>
<td>Ethnic Change</td>
<td>.024</td>
<td>.681</td>
<td>4.142***</td>
<td>4.161***</td>
<td>3.367***</td>
<td>1.793***</td>
</tr>
<tr>
<td></td>
<td>(.223)</td>
<td>(.495)</td>
<td>(1.116)</td>
<td>(1.108)</td>
<td>(1.737)</td>
<td>(.218)</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>559</td>
<td>559</td>
<td>559</td>
<td>559</td>
<td>559</td>
<td>32065</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>.005</td>
<td>.008</td>
<td>.028</td>
<td>.052</td>
<td>.095</td>
<td>.062</td>
</tr>
</tbody>
</table>

*p<.05; **p<.01; ***p<.001
We next proceed to examine different formulations of the dependent variable which permit more of the variation in the source coefficients to be expressed. In addition, we restrict our attention in Table 2 to significant source coefficients. The logistic regression on the threat dummy in column 1, Table 2 confirms the pattern noted in Figures 4 a-h, with geographic unit size and its cubic form negatively associated with the diversity-threat relationship while the squared term is positively related. Ethnic change also predicts a stronger, positive, diversity-threat relationship. Restricting the sample to significant source coefficients improves model fit: the logistic regression in the table has a pseudo $R^2$ of .093, which compares with a fit of just .052 for model 4 in Table 1. The ordered logistic and linear regression variants of the model (columns 2 and 3) reveal a similar relationship. This is confirmed in the weighted model in column 4 of the table which displays similar effect sizes to those in column 3.
Table 2. Models of Positive Diversity-Threat Association (Significant Input Coefficients Only)

<table>
<thead>
<tr>
<th></th>
<th>Logistic</th>
<th>Ordered Logit</th>
<th>Linear Regression</th>
<th>Linear Regression (Weighted)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Geographic Size</strong></td>
<td>-2.719*</td>
<td>-2.904*</td>
<td>-.561**</td>
<td>-.389***</td>
</tr>
<tr>
<td></td>
<td>(1.051)</td>
<td>(1.170)</td>
<td>(.195)</td>
<td>(.024)</td>
</tr>
<tr>
<td><strong>Geography squared</strong></td>
<td>.593**</td>
<td>.602*</td>
<td>.119**</td>
<td>.077***</td>
</tr>
<tr>
<td></td>
<td>(.221)</td>
<td>(.246)</td>
<td>(.041)</td>
<td>(.005)</td>
</tr>
<tr>
<td><strong>Geography cubed</strong></td>
<td>-.036**</td>
<td>-.035*</td>
<td>-.007**</td>
<td>-.004**</td>
</tr>
<tr>
<td></td>
<td>(.014)</td>
<td>(.015)</td>
<td>(.003)</td>
<td>(.000)</td>
</tr>
<tr>
<td><strong>Ethnic Change</strong></td>
<td>1.349**</td>
<td>1.474**</td>
<td>.224**</td>
<td>.247***</td>
</tr>
<tr>
<td></td>
<td>(.424)</td>
<td>(.453)</td>
<td>(.067)</td>
<td>(.009)</td>
</tr>
<tr>
<td><strong>Year Fixed Effects</strong></td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>3.648*</td>
<td>-</td>
<td>1.113**</td>
<td>.945***</td>
</tr>
<tr>
<td></td>
<td>(1.472)</td>
<td></td>
<td>(.409)</td>
<td>(.041)</td>
</tr>
</tbody>
</table>

\[ N = 252 \]

\[ \text{Pseudo } R^2 \text{ or } R^2 = .093 \]

*p<.05; **p<.01; ***p<.001

We can go further and restrict our sample to studies which focus only on native-born white respondents. Table 3, which repeats the strategy deployed in Table 2, shows essentially the same pattern, albeit with improved model fit. The model fit is now reaching .40 - around .29 when fixed effects are excluded (not shown). We thus find a very powerful, parsimonious model of the variables which moderate the diversity-threat relationship. It also speaks to our recommendation that studies always include a model restricted to native-born whites. At the very least models should test a full set of cross-level interactions between ethnicity and
contextual diversity using white x diversity interactions to make comparisons with the
literature.

Table 3. Models of Positive Diversity-Threat Association (Significant Input Coefficients Only),
Native White Samples Only

<table>
<thead>
<tr>
<th></th>
<th>Logistic</th>
<th>Ordered Logit</th>
<th>Linear Regression</th>
<th>Linear Regression (Weighted)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographic Size</td>
<td>-4.336**</td>
<td>-5.809**</td>
<td>-.969***</td>
<td>-.830***</td>
</tr>
<tr>
<td></td>
<td>(1.516)</td>
<td>(1.978)</td>
<td>(.246)</td>
<td>(.032)</td>
</tr>
<tr>
<td>Geography squared</td>
<td>.927**</td>
<td>1.235**</td>
<td>.213***</td>
<td>.176***</td>
</tr>
<tr>
<td></td>
<td>(.328)</td>
<td>(.429)</td>
<td>(.056)</td>
<td>(.007)</td>
</tr>
<tr>
<td>Geography cubed</td>
<td>-.055**</td>
<td>-.074**</td>
<td>-.013**</td>
<td>-.010***</td>
</tr>
<tr>
<td></td>
<td>(.021)</td>
<td>(.028)</td>
<td>(.004)</td>
<td>(.000)</td>
</tr>
<tr>
<td>Ethnic Change</td>
<td>1.768*</td>
<td>2.178**</td>
<td>.311**</td>
<td>.266***</td>
</tr>
<tr>
<td></td>
<td>(.692)</td>
<td>(.813)</td>
<td>(.097)</td>
<td>(.014)</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Cons</td>
<td>5.550**</td>
<td>-</td>
<td>1.192*</td>
<td>1.041***</td>
</tr>
<tr>
<td></td>
<td>(2.055)</td>
<td>(.497)</td>
<td>(.047)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>118</td>
<td>118</td>
<td>118</td>
<td>6439</td>
</tr>
<tr>
<td>Model Fit (Pseudo R² or R²)</td>
<td>.211</td>
<td>.393</td>
<td>.394</td>
<td>.439</td>
</tr>
</tbody>
</table>

*p<.05; **p<.01; ***p<.001

Trust and Cohesion

Though social trust and cohesion were not the focus of our meta-analysis, we included 8 such articles, representing 23 of our 558 coefficients. As trust and cohesion findings did not stand out from those for opposition to immigration and support for the populist right, we wished to ascertain whether our model fit van der Meer and Tolsma’s (2014) meta-data on the relationship between contextual diversity and trust/cohesion. Van der Meer and Tolsma reported no significant relationship between
the size of the geographic unit and the diversity-solidarity relationship, but our work will show that, for national-level outcomes, a 3rd-order polynomial model fits the data.

These authors’ data were collected using different selection criteria, with model results summarized for particular articles or models as supporting either threat (i.e. diversity significantly reducing solidarity), or otherwise. Just two studies are common to both of our datasets. There is one record per article or model rather than separate records for each coefficient and data are scaled to a coarser geographic classification than our own. Geographic identifiers are not estimated on the basis of average population, so the size of a category such as neighbourhood or municipality varies somewhat (Van der Meer and Tolsma 2014: 463). The comparison between our datasets is therefore imperfect.³

In their analysis, the authors claim, correctly, that geographic units are not significantly associated with diversity threat. However, this is mainly because many of the dependent variables in their meta-analysis are expressed locally, including volunteering, trust in neighbours and associational membership. Higher neighbourhood diversity tends to be associated with lower local solidarity but tends not to affect, or even increase, national solidarity – notably when the dependent variable is the national/general question ‘in general, can people be trusted’ (Van der Meer and Tolsma 2014: 470). In contrast, our measures – immigration attitudes and support for the radical right– concern orientations to national issues and actors. The best point of comparison with our meta-analysis, therefore, is generalized trust in outgroups. Unfortunately, there are no studies in the van der Meer and Tolsma
data focused only on generalized trust in outgroups. However, 42 studies in their data use trust in people in general as the outcome of interest. We would expect exposure to minorities to reduce general trust, via Putnam’s ‘hunkering down’ anomie mechanism (Tolsma and van der Meer 2016), while contact should increase it - thus we should see a similar relationship to that plotted with our data in Figures 1-3.

Taking the 42 studies which ask about generalized trust, a more national-scale attitude, the relationship, shown in Figure 5, looks similar to that in our data, as plotted in Figures 1-4. Even if we discount the lowest level of geography, the pedestrian ‘egohood’ of 250 metres, because this is based on the Dinesen and Sonderskov study which is also in our dataset, there is still a pattern in which threat is low at neighbourhood level, rises to a peak for regions, and declines at country level.
The main difference from our data regarding immigration attitudes and populist radical right voting is that van der Meer and Tolsma only record a threat effect if all diversity-solidarity relationships in an article report a significant inverse correlation between diversity and solidarity. This is a stringent test which does not reveal whether coefficients that did not support the threat hypothesis significantly supported contact, or were not significant in a positive or negative direction. Our methodology would add insignificant results signed in the direction of threat to the cases underpinning the curve in Figure 5. This would undoubtedly shift it upwards, revealing a pattern even more similar to Figures 1-3.

We model the main moderators of the diversity-solidarity relationship in Table 4, discarding 3 cases where results were mixed, to yield 39 cases for analysis. Here we focus on replicating our 3rd-order polynomial formulation based on the size of the geographic unit. The dependent variable is a
dummy variable taking the value of 1 for diversity predicting threat (low trust) enhancement and 0 for diversity predicting no significant reduction of trust. A summary of model results, rather than actual coefficients, comprise the data points. Geographical units run from the smallest, 1, used to describe Dinesen and Sonderskov’s 250-metre radius ‘egohoods’ (also present in our study), to 4, country.

The first point to notice is that while geographic unit size has no linear association with the diversity-threat relationship, the 3rd-order polynomial form shown in model 3, in which threat falls, rises, then falls with scale, is significant, and it nearly triples model fit. Note also that, as with our data, 4th and higher order polynomial formulations are not significant. Models include a control for studies which cluster standard errors on geographic units, as opposed to either aggregate or unclustered individual-level studies. This variable inversely predicts a diversity-threat result, but does not affect the coefficients of the geographic size parameters comprising our cubic wave model.
<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographic Size</td>
<td>-.180 (.079)</td>
<td>-.164 (.961)</td>
<td>-33.54** (12.485)</td>
</tr>
<tr>
<td>Geography squared</td>
<td>-.001 (.076)</td>
<td>5.273** (1.947)</td>
<td>5.516** (1.940)</td>
</tr>
<tr>
<td>Geography cubed</td>
<td>-.265** (.097)</td>
<td>-.278** (.097)</td>
<td></td>
</tr>
<tr>
<td>Dependent variable geographic size</td>
<td>.782** (.265)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cluster Correction</td>
<td>-1.820*** (.464)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>/cut 1</td>
<td>-1.761 (.527)</td>
<td>-1.715 (2.695)</td>
<td>-67.814 (25.041)</td>
</tr>
<tr>
<td>/cut 2</td>
<td>.478 (.502)</td>
<td>-.431 (2.690)</td>
<td>-66.440 (25.009)</td>
</tr>
<tr>
<td>N</td>
<td>120</td>
<td>120</td>
<td>120</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>.002</td>
<td>.002</td>
<td>.063</td>
</tr>
</tbody>
</table>

The above indicates that micro-threat, contact, macro-threat and country fixed effects behave similarly between the two datasets. In the smallest geographies, micro-exposure is higher than contact, increasing opposition to immigration and reducing generalized trust. At neighbourhood level, exposure falls below contact, calming immigration fears and increasing generalized trust. Diversity at higher geographies, where macro-threat exceeds inter-ethnic contact, is associated with an increase in white immigration fears and lower generalized trust.
Discussion

The linear relationship between ethnic change and white threat responses accords with perspectives from political psychology which characterize change as a shock to the cultural, economic or political security of ethnic majority populations – especially their conservative members. Change is thus more likely to evince a threat response than ambient levels of diversity (Newman 2013; Stenner 2005). We have seen that the relationship between geographic size and diversity threat is not similarly linear but takes a cubic form as the size of the areal unit increases. How can we best explain this wave function?

Neighbourhood minority share greatly increases the likelihood that whites will have minority friends: moving from a ward that has no ethnic diversity to one where minorities comprise a 50% share of the population more than doubles a White Briton’s probability of having minority friends. This reduces opposition to immigration (ONS and Home Office 2011). The results of a meta-analysis of the inter-ethnic contact literature in psychology show nearly universal positive effects of diversity on out-group attitudes (Pettigrew and Tropp 2006). Yet these studies almost all involve small-scale settings, such as the classroom or laboratory. As such, they are designed to capture regular, intensive contact with out-groups rather than intermittent exposure, which is the more common experience in diverse geographies, especially at larger scales.

What is occurring in large geographies? Here our findings are consistent with evidence from those who claim that larger geographical units such as counties, states or nations are where economic
and political contestation takes place. By contrast, one is unlikely to perceive oneself as competing
with a neighbour for jobs or political power (i.e. Ha 2010: 30; Abrajano and Hajnal 2015). The fact
that the politics that counts is not local, and mass media operates more efficiently at larger economies
of scale, means people pay more attention to city, state or national media than local news. In addition,
larger units such as regions or nations figure more centrally for people’s sense of ontological
(existential) security than locales (Skey 2011). Nations inculcate an emotional attachment to myths
and symbols much more than locales do. People may move neighbourhood but emigrate much less
often. They may risk their life for the nation, but rarely for their town. While local change may be
unsettling, change at the national level could be perceived as an existential threat. This distinction is
reflected in polling data in the United Kingdom where respondents who are relaxed about local
immigration nevertheless express great concern about its effect on the nation. 51% of British
respondents say immigration is a problem nationally but not locally while just 8% say the reverse.
This holds almost as much for whites in diverse locales as in homogeneous ones so is not an artefact
of whites’ less diverse residential contexts. As a comparison, the local-national concern gap over
crime, the next highest perception gap, is just two-thirds as large as for immigration (Frere-Smith
2014: 90-91). Likewise, the share of Americans who feel immigration is changing the nation a lot is
over twice as high as those who think it is changing their communities a lot (PRRI/Brookings 2016: 48)
While contact in local areas and threats to politics and identity in larger units are plausible explanations for the rising middle part of the curve (squared unit size), the negative relationship at the ends of the geographic scale (linear and cubed unit size) challenge conventional explanations. Our view is that more research is needed at the micro-level, on geographical units of fewer than 1,000 residents, and, using a longitudinal approach, on large-scale geographies of more than 500,000. These surveys are the only studies of exposure to diversity at the micro level that we could find. Since we completed our analysis, a paper on diversity and social solidarity by Tolsma and van der Meer (2016) replicated Dinesen and Sonderskov’s results for the Netherlands, providing further evidence in support of micro-threat.

Our cubic model is, moreover, robust to excluding micro-scale studies. The reason is evident in Figures 4a–h, where the next level of geography - of 1,000-5,000 people - scores consistently higher in diversity threat than units of 5,000-10,000 population. Both are represented by nearly 20 studies (500,000 data points) in our sample. This again suggests that micro-threat is operating. Note as well that this problematizes the view that selection effects - the ‘white flight’ of anti-immigration whites from diverse locales but not out of diverse wider geographies – explains why diversity threat is elevated in larger units. All of which comports with evidence that anti-immigration and radical right-voting whites are only slightly more likely to move toward whiter wards than liberal whites (Kaufmann and Harris 2015).

---

2 There may therefore be a difference in diversity’s micro effects between studies of solidarity (exit) and opposition to immigration (voice).
If psychological discomfort explains micro-threat and the preponderance of contact over micro-threat accounts for reduced white anti-immigration sentiment at meso level, what explains the final curve in the cubic wave in the last column of Figures 4a-h? Specifically, how can we make sense of the dip in threat beyond units of approximately 1 million people? Here the most likely explanation concerns the unobserved characteristics which correlate with both threat and diversity in large units. Comparing diversity and immigration attitudes between Sweden and Greece is difficult because the particularity of these countries shapes both their diversity and attitudes toward immigration. This is also the case for regional ‘nations’ such as Quebec or Flanders, whose residents are somewhat more opposed to immigration than other Canadians or Belgians; or Scotland and Catalonia, where the reverse is true. This may be because some stateless nations are formed on an ethno-linguistic basis while others originally coalesced around political traditions (i.e. Brubaker 1992); or due to regional nations adopting an opposing stance to that of the central government.

An analogous pattern obtains in other distinctive large jurisdictions (i.e. East Germany, New Mexico). We surmise that cities are less bound by this kind of particularity because power and national identity have usually operated above the level of the city. The best method for addressing these unit effects is to use fixed effects models with longitudinal data, which controls for unspecified characteristics of units. In this vein, it is noticeable that virtually all country-level longitudinal coefficients in our dataset (27 of 31) report a positive relationship between diversity and threat, with over two-thirds (21/31) finding a significant positive effect.
To summarize: we posit three major influences on diversity threat: micro-threat, contact and macro-threat. These are represented as linear functions in Figure 6. The curve of micro-threat (t) drops rapidly as the size of a diverse unit increases beyond block level while the contact line (c) declines more gradually because opportunities for whites to mix and make friends in local institutions such as schools, shops and churches remains high as one moves from a diverse block to a diverse neighbourhood. Micro-threats (t) exceed contact effects (c) until inflection point a, leading to falling net threat levels in the lower-middle range of the spatial scale. As we move beyond the neighbourhood, opportunities for contact decline while macro-threat (T) rises. Contact (c) predominates over micro- (t) and macro- (T) threats until inflection point b is reached, beyond which point macro threats (T) exceed contact effects (c). Increasing media attention, inter-ethnic competition for resources and power, and perceived challenges to the symbolic boundaries of salient identities come together to increase threat perceptions. The final curve in the cubic polynomial takes place at the highest geographies on the far right of the diagram, but we omit it because we believe it occurs for methodological rather than substantive reasons.
Conclusion

In this article we have presented results from a meta-analysis of nearly 200 articles encompassing over 500 coefficients and 5 million data points on the relationship between ethnic diversity and public attitudes toward immigration and electoral support for the anti-immigrant radical right. In addition our study encompassed a small sample of work on trust and solidarity. We find support for both threat and contact theory, with each holding sway at a different geographic level.

The preponderance of studies (over 70%) reporting significant results find that diversity increases opposition to immigration and electoral support for populist radical right parties among native-born whites. However, our principal finding is that geographic scale moderates the
relationship between diversity and threat, producing a cubic polynomial curve of diversity-threat. As the scale of geographical units increases, threat first declines, then, beyond units of between 50,000-100,000 people, again begins to rise. As units exceed a population of around 1 million people perceptions of threat again begin to subside.

While further research is required we posit three substantive drivers of the diversity-threat relationship that operate with varying degrees of force depending on the scale of analysis: micro-threat, contact and macro-threat. The balance between these processes alters as scale increases, which explains the first three sections of the cubic wave. By contrast, the decline in threat at the highest scale arises, we argue, from unspecified time-invariant characteristics of regions and nations. Accordingly, longitudinal work at national level, which does not suffer from this bias, uncovers an overwhelmingly positive relationship between diversity and threat. The vast majority of studies which examine ethnic change also find that increased diversity is associated with higher white threat perceptions. In our meta-analysis we successfully fit this model to existing meta data on the diversity-solidarity relationship, uncovering a similar pattern. Our work suggests there is a common underlying relationship between diversity and a range of ethnic threat variables.

Finally, we make a number of recommendations for further work in the field. First, scholars should report separate results for white, native-born samples or, at the very least, for interactions between diversity and ethnicity. Second, we urge researchers to simultaneously test for levels of, and
changes in, diversity. Third, researchers should include two or more parameters for ethnic context, preferably one for units in the 1,000-50,000 population range and one for those over 100,000. Fourth, more research is needed at the smallest and largest scales. Finally, in large contexts, more longitudinal work with fixed effects models is required to assess one of the great questions of our time: whether rising levels of ethnic diversity will stoke white majority fears.
References


Surowiecki, J. (2004). *The wisdom of crowds : why the many are smarter than the few and how collective wisdom shapes business, economies, societies, and nations.* New York, Doubleday
Notes

1 Note that we correct for question wording since questions on some surveys elicit opinion on the benefits of immigration and others on its drawbacks. So too for trust and cohesion questions. We also alter the direction of the observed relationship when context is measured as % native whites rather than % minorities. In some cases odds ratios are reported rather than coefficients: those below 1 are coded as negative relationships.

2 In stata, frequency weights must be integers so we inflate rather than deflate the data and multiply by a factor of 10 to 180.

3 We omit three cases in which segregation is used to measure diversity.

4 There are, of course, numerous studies of intensive contact in small settings (summarized in Pettigrew and Tropp 2006).
Appendix 1 –Selection Criteria and Bibliography

Selection Criteria

Studies included in the meta-analysis had to meet several inclusion criteria. First, we only considered studies that specifically include data on ethnic context. Second, with regard to studies on the populist radical right we exclude those that examine the individual-level and neglect ethnic context. Studies were selected using major search engines and bibliographic tracing tools. The published articles, books, dissertations and working papers examined relationships between ethnic diversity and either a) opinion of immigrants, immigrant minorities or immigration; or b) electoral or membership support for radical right parties. The scope of our study does not extend to native minorities such as Roma or African-Americans though we include 6 of these studies for exploratory purposes to examine whether similar relationships could be observed. Also for exploratory purposes, as noted, we included 13 tests across 6 papers on questions of social solidarity (trust/cohesion) and 20 tests on questions of out-group antipathy that are difficult to classify. We focus only on the post-1995 period while accepting that many important works were conducted prior to this date. Future researchers should be able to build on our data in whichever directions they choose to expand our collective purview even further. We do not always include all ethno-contextual parameters, especially when large number of closely-related parameters were tested (i.e. % Indian, % African). We also avoided reporting interactions.

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